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Improving road asset condition monitoring

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Abstract

Road networks often carry more than 80% of a country's total passenger-km and over 50% of its freight ton-km according to the World Bank. Efficient maintenance of road networks is highly important. Road asset management, which is essential for maintenance programs, consist of monitoring, assessing and decision making necessary for maintenance, repair and/or replacement. This process is highly dependent on adequate and timely pavement condition data. Current practice for collecting and analysing such data is 99% manual. To optimize this process, research has been performed towards automation. Several methods to automatically detect road assets and pavement conditions are proposed. In this paper, we present an analysis of the current state of practice of road asset monitoring, a discussion of the limitations, and a qualitative evaluation of the proposed automation methods found in the literature. The objective of this paper is to understand the issues associated with current processes, and assess the available tools to address these problems. The current state of practice is categorized into: 1) type of data collected; 2) type of asset covered and 3) amount of information provided. The categories are evaluated in terms of a) accuracy; b) applicability (efficiency); c) cost; and d) overall improvement to current practice. Despite the methods available, the outcome of the study indicates that current condition monitoring lacks efficiency, and none provide a holistic solution to the problem of road asset condition monitoring.

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Keywords: Road condition; road defects; road maintenance; road monitoring; automation

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1. Introduction

One of the global grand challenges (2013) identified by the UK Royal Academy of Engineering, the US National Academy of Engineering and the Chinese Academy of Engineering is to maintain, restore and improve urban infrastructure. Local streets and highways are identified as critical transportation conduits as part of the urban infrastructure. Road networks enable growth, mobility and contribute to economic prosperity, productivity and wellbeing (Cook 2011; DfT 2013b). The Highways Agency (2012) reported that monitoring the road network is essential due to its great value as a public asset.

Developed countries have millions of kilometres of road network mainly consisting of asphalt and concrete varying in surface condition, age and performance. Several countries report issues with the current state of its network. The American Society of Civil Engineers (2013) has graded the country’s network with a D (A is the best score), based on its poor condition. The same grade is given to the local transport networks of the UK by the Institute of Civil Engineers (2014). Business organizations, whose interest is directly associated with the state of the roads, often express concerns and dissatisfaction with the current conditions. Repeated studies performed by the Confederation of British Industry (2011; 2014) showed that in the UK, more than 50% of business leaders compare the country’s transport network unfavourably to international standards. The study claimed that the network has been deteriorating in the past 5 years. Almost 50% of UK citizens identify the urgency of changing the way roads are maintained. One of the objectives set by the Institute of Engineers (2014) for 2018 is to reduce the maintenance backlog on local roads and adopt a regime that will result in preventive maintenance.

The International Infrastructure Maintenance Manual (2006) states that the initial requirements for an asset management system is to have *knowledge of the existing assets*, *status of their condition* and *the level of service they provide*. Road condition assessment is an essential task when designing, planning and determining the appropriate maintenance program required, since the latter is dependent on the former. The Department for Transport and the Highways Agency (2014) report that road condition data is insufficient and gaps exist in the information collected. One of the reasons is the lack of quality control of data collection. Based on a study funded by the National Cooperative Research Program (2009), in the USA, only 35% of Departments of Transport have protocols in place for road condition assessment. Additionally, the frequency of data collection necessary for road condition assessment depends on the size of the network (owned by each authority), varying once every one to four years. This has led to insufficient data collection of existing road networks, and insufficient protocols for inspection and monitoring of road networks. Therefore, the need for an efficient asset management system is required for sufficient road condition assessment, as well as improving the overall inspection and monitoring of road networks.

1.1. Current state of practice in road condition monitoring

Road condition monitoring consists of four main steps (Fig. 1). The goal is to capture the longitudinal and transverse profiles, the condition of the edge of the road and the texture of its surface. The first step of the process is data collection, either automatically or manually. For automated data collection, specialized vehicles equipped with several sensors such as laser scanners, road profilers, accelerometers, image and video cameras and positioning systems (DfT 2011) are used. Due to the complexity of these vehicles, the cost to purchase (minimum £500,000), operate and maintain are high (Werro 2013). For these reasons, their usage is restricted as a road assessment tool, which happens once a year and only on highways. Consider the case in the UK, where the strategic road network represents 9.6% of the country’s entire network (DfT 2013a), this is translated to only 0.2% of the total volume of inspections; the other 99.8% is manual inspection.

Fig. 1. Road condition monitoring process.

These inspections are performed by accredited surveyors by either walking or driving along the roadway in search of defects. If defects are detected, they are assessed and if possible, addressed. At the end of the inspection, all gathered information need to be inserted into the road authorities' central database. Therefore, inspectors are required to upload the data collected. The data collected consist of images, descriptions, and treatments of each defect. If the defect could not be addressed during inspection, the inspector is responsible to assign a priority rating for repair to the defect. Based on the description of the process, it is obvious that manual visual surveys are time consuming, laborious and inefficient.

Some local road authorities, such as counties, rely on road users for collecting road related information. Several UK counties have online reporting tools where citizens can report defects on the roadway. This helps authorities be alerted, since usually the defects reported are of high severity and need urgent attention. However, attention is also necessary to medium severity defects so that they are treated on time and not left to deteriorate further. Thus, the responsibility of road pavement monitoring should be at the authority level. More inspection and monitoring is necessary to prevent against such defects.

In the case of automated data collection, defects need to be detected within the scene. At this stage, inspectors are viewing and assessing the severity of the defects. There are three levels of severity: low, medium and high. Although, well-written defect detection guidelines are followed for the step of assessment, Bianchini et al. (2010) have shown that subjectivity is inevitable since there is a lack of baseline for the severity of defects. The same limitation holds for the case of manual visual surveys when the inspector needs to assess the severity of a defect on the spot. The guidelines hinges on rating the severity of the defect based on the three levels, which everyone treats differently. Finally, road segments are assigned a Road Condition Index (RCI). This is calculated based on the type, number and severity of defects. RCI is then used for classifying road segments according to national standards (DfT 2011).

This paper aims to investigate the current state of research related to the subject of automating the road condition monitoring process and the efforts to address the limitations it faces. Proposed methods are assessed based on their accuracy, efficiency and cost. On top of those criteria, proposed methods are evaluated according to the amount of their contribution in improving the current practice and how many limitations they are overcoming.

2. Research in automated road defect detection, assessment and repair

Several research efforts have been focusing on automating defect detection, assessment and repair. Those can be classified using three criteria (see research cube in Fig. 2). One is according to the defect that they are focusing on (depicted in axis x of the research cube). The general defects category in axis x corresponds to methods that either focus on the "roughness" of the road or are restricted to presence. Both of these types of methods are discussed below. The second is based on the type of data used for collecting information (depicted in axis z of the research cube). Finally, they can be categorized based on the level of detail they reach (depicted in axis y).

The first level of detail is called presence. Presence is the category that answers to the question of whether a defect exists in the given data. An example of the outcome of such a method can be seen in Fig. 3a. The second level of detail provides the additional information of where the detected defect is located within the given data. This level is called detection. Such an example on visual data can be seen in Fig. 3b. The final level of detail is measurement. Those methods are capable of automatically calculating the attribute necessary to describe the severity of a defect. In the case of longitudinal cracks, the attributes used to describe it are its width and length.

2.1. Vision data based methods

Several methods proposed in the literature operate on 2D images. Cord and Chambon (2012) and Nguyen et al. (2009) presented approaches that generally classify images between defective and non-defective, but were only tested for cracks. Another similar method was created by Zhou et al. (2006). Zhou's method is accurate enough and considers various road defects. Its limitation is that it is restricted to the level of presence.

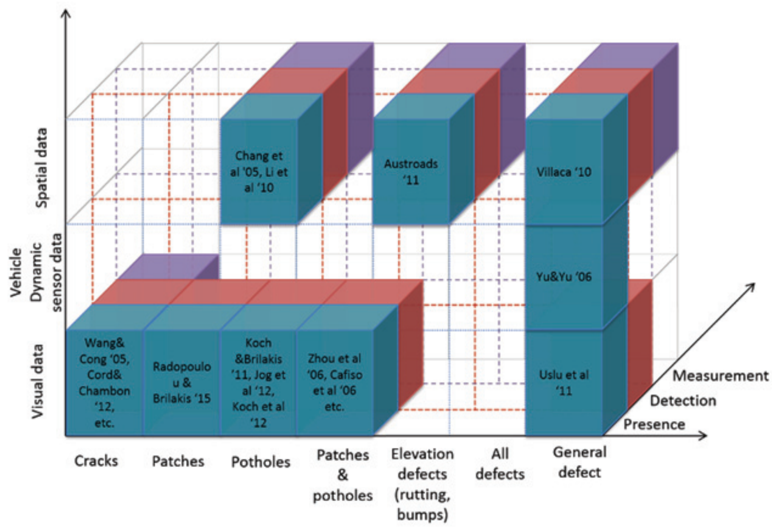

Fig. 2. Research cube: Methods for automating defect detection, assessment and repair.

Extensive research has been performed in regards to the defect of cracks. Specifically, methods that perform crack classification (Moghadas Nejad and Zakeri 2011; Salari and Bao 2011; Ying and Salari 2010), depth estimation (Amarasiri et al. 2009) and even sealing (Kim et al. 2009) have been presented. Tsai et al (2009) conducted a comparison study of several methods that perform image segmentation for crack detection and classification. Segmentation refers to partitioning the image in multiple segments based on similar characteristics. The comparison showed that none of the methods is comprehensive and robust.

Besides cracks, other defects have also been investigated on how to be detected using 2D images. Yao et al. (2008) have proposed a method for detecting patches but the success of the method is low. Battiato et al. (2007) have also worked on patches, however their method can’t tell the difference between a patch and a pothole. Radopoulou and Brilakis (2015) created a method for detecting and tracking patches in asphalt video data. Lin and Liu (2010) utilized texture information for differentiating potholes from cracks. Koch and Brilakis (2011) did the same along with using shape information for detecting potholes in asphalt images. Koch et al. (2012) extended this work for detecting potholes in video data. Jog et al. (2012) worked one level deeper to measure the properties of potholes.

Other methods that operate using images are 3D reconstruction methods that utilize the notion of stereo-vision. Stereo-vision offers the possibility of reconstructing the surface with the aid of multiple video cameras. Hou et al. (2007) and Wang (2007) experimented the applicability of such a technique for the purpose of road reconstruction. Additionally, Uslu et al. (2011) and Balali and Golparvar-Fard (2015) used it in a study for enhancing a method for highway condition assessment. However, this method focuses on detecting highway related assets such as asphalt in general, road marking, guardrails etc. Vilacca et al. (2010) used stereo-vision for understanding the road texture. Finally, Chang et al. (2005) applied it for measuring the depth of potholes and calculating the necessary filling material, Wang and Gong (2007) for detecting and classifying cracks and Yu et al. (2007) for calculating crack depth.

2.2. Spatial data based methods

Such methods use range sensors for collecting data and analyzing them. Li et al. (2010) created a system which combines a Gigabit Ethernet digital camera assisted by an infrared laser line projector for detecting rutting and shoving, defects related with the z-axis of the road. The projector covers the transverse profile of the road lane while the camera captures its image. Calibration of the sensors is required before data collection begins. The point clouds produced are further processed for defect detection whereas the digital images assist in the post-verification of the final outcome.

Fig. 3. (a) Results of a "presence" method. (b) Results of a "detection" method.

A similar approach was proposed by Laurent et al. (2012), which is adopted by Pavemetrics Systems Inc. This approach uses laser line profilers and high speed cameras mounted on the back of a van to simultaneously acquire the 3D profile of the road and 2D images of it. Traffic isn't disrupted, since the van can travel up to 100km per hour. It can also operate at any time of the day, since it is insensitive to lighting conditions. Specialized software is then used for automatically detecting various types of defects. Another similar method was proposed by Chang et al (2005) for the purpose of detecting potholes only.

2.3. Vehicle dynamic sensor data based methods

Vehicle dynamic sensor data based methods focus on understanding the roughness of the road or estimating the road profile. Yu and Yu (2006) proposed a vibration-system for performing preliminary road condition surveys. Their main finding was that the mechanical responses of vehicles captured by accelerometers could help in understanding the road's roughness. The advantage of those sensors is that the data they collect require small storage units and also can be processed in real-time. However, such a method requires that the surveying vehicle's service condition is calibrated, otherwise the results can't be compared.

Lakusic et al. (2011) also used accelerometers for understanding the road roughness. However, the scope of this study was to understand the difference before and after road construction, at railroad intersection and on the effect of tram track roads. This study showed that for detecting defects, more than two accelerometers are required. Harris et al. (2010), Ngwangwa et al. (2010), Gonzalez et al. (2008) and others have also used those sensors for the purpose of reconstructing the road profile. For the same purpose, Doumiati et al. (2011) tested the use of suspension deflection sensors, Johnsson and Odelius (2012) measured the tire noise with microphones and Wang et al. (2013) measured the tire pressure.

3. Synthesis

This paper's objective is to perform a qualitative evaluation of proposed methods that aim to automate road defect detection, assessment and repair (see table 1). The motivation of this study is to understand the reasons behind the poor road conditions of several developed countries and identify the gaps of knowledge within the state of research. The criteria used for assessing the proposed methods in the literature are:

- Accuracy: how accurate the produced results are
- Applicability: how efficient and easy it is to apply the method.
- Cost: equipment, installation and maintenance cost
- Contribution: how much of the current practice limitations' each method is overcoming.

The proposed methods found in the literature aren't equivalent. Hence, best effort was made for the comparison to remain general and fair. Methods are compared with an ideal solution. This would be an accurate, easy to apply and use, low cost solution that addresses all limitations addressed in the current practice.

Current research has given great emphasis to logarithmic accuracy. Most vision based methods that operate in 2D images address this criterion. Their performance achieves accuracies of more than 80%. There are a few though that do not perform as well and provide lower accuracy results. 2D image based methods' applicability varies based on the setup required. It can be as easy as attaching one camera to the rear of a car. However, it can be more complicated if it needs to be positioned at a specific height, hence requires a van to be attached, along with specialized sensors for addressing other limitations. In regards to their cost, it also varies according to the specific setup. Some methods use parking camera and the cost is low (~£500). Others though use specialized cameras for which the cost is significantly higher (such as line scan camera that costs ~£1,500). As aforementioned, if additional sensors such as laser-based illuminators are required, then the cost increases (from £50 to £100 more). In those cases, the applicability is also affected because the system gets more complicated. The main disadvantages of such methods are in relation to their contribution in overcoming the limitations of current practice. On one hand, these methods are restricted to identifying only surface defects with the exceptions of potholes. Elevation defects such as rutting and sagging can't be detected. Also, these methods are single class. Single class means that focus is given to one or a couple of defects only. Thus, they aren't efficient enough to be adapted in reality as they are partially contributing to the automation of defect detection and assessment.

Table 1. Performance of methods for automated defect detection, assessment and repair.

		Accuracy	Applicability	Cost	Contribution
Vision data based methods	2D	accurate (most of them)	depends on the setup, easy - medium	medium	partial
	3D	accurate	depends on the setup, medium	medium	partial
Spatial data based methods		accurate	require specialized vehicles to be attached to	high	partial
Vehicle dynamic sensor data		accurate	require pre-calibration with vehicle	low	partial
Ideal solution		accurate	easy	low	overcomes all limitations

The limitation of detecting elevation defects is faced by methods that use stereo vision and reconstruct the road profile. However, these methods have an increase in their cost since they require multiple sensors (minimum 2, some methods require 4). The amount of this increase depends on the total number of cameras that are needed. Also, the type of camera used affects the total cost of the system. Line scan cameras are more expensive than area scan cameras. The resolution is another factor that affects the cost. The higher the resolution needed, the higher the cost of the camera. The number of sensors affects the complexity of the system, hence those methods can become more difficult to apply and this impacts applicability negatively. The use of multiple cameras requires their calibration before data collection. This is necessary for synchronizing the sensors, which provides the ability of correlating the collected data from each sensor. Calibration translates to extra time consumed and increase of the method's complexity.

Spatial data based methods are very accurate but they are expensive. Not only the sensors themselves have a high cost to purchase (~£3,000), but they also need to be mounted on specialized vehicles. Hence, the cost is increased further when assembling and operation is considered. On the other hand, complexity is also increase, which in turn affects the applicability of those methods in a negative way. In the case of laser scanners, a Cartesian point cloud information is produced. With such information only elevation defects can be detected. So, laser scanner based methods can also be characterized as single class. In contrast, stereo vision methods can additionally extract semantics (image features, geometric characteristics). Last, laser scanners suffer from mixed-pixel phenomena. This is one type of noise in data that is required to be removed while post-processing (Kiziltas et al. 2008).

Vehicle dynamic sensor data based methods use sensors that are quite cheap. An accelerometer costs approximately £30 and a suspension deflection sensor costs approximately £250. Both prices are cheaper than the cameras used in 2D visual data based methods. The applicability of the sensors is easy. They only need to be attached on the vehicle that collects data, which can be of any type (passenger car or van). As aforementioned, they also provide the advantages of requiring little storage for saving the collected data and being able to process in real time. Their limitation is that they are considered as single class methods as well. This is due to their application only on elevation defects. They can also provide qualitative information in regards to the road's roughness. So, such methods contribute partially to the limitations of current practice.

4. Conclusions and recommendations

This paper analyzes the current practice of road condition monitoring. The whole process can be summarized in four main steps. First is data collection, which can be performed either manually or automatically. For automated data collection, specialized vehicles are used. Due to their high cost of purchase and operation, their usage is restricted leaving thousands of kilometers to be inspected with traditional manual visual surveys. Unfortunately, such surveys are time consuming, laborious, subjective and frequent enough. The same limitations are also found in the following steps of the process which are the detection of defects and the assessment of severity. Finally, the RCI of road segments are calculated in order to classify roads based on national rating standards and efficiently decide on maintenance and/or rehabilitation programs.

In this paper the current research for automating road defect detection, classification and repair is presented. The objective is to perform a qualitative evaluation of all proposed methods. The criteria used for the analysis are accuracy, applicability, cost, and contribution to the encountered issued.

In general, none of the current approaches are multi class. All methods are either concentrating on one defect or just a couple. Vision based methods operating on 2D images are limited to surface defect. 3D reconstruction based methods address this limitation, however they are just capable of detecting some defects and not all of them simultaneously. The same holds for laser scanning methods. Moreover, such approaches require the use of specialized vehicles to collect data, which is unattractive due to its high cost. As for vehicle dynamic sensor based methods, those are limited to rough pavement defect detection. It has been proven that such sensors can facilitate the calculation of the road roughness, however no more information regarding specifics of defects can be provided at the moment.

All methods found in the literature have multiple benefits, with most of them covering the demand of algorithmic accuracy. However, the limitation of all is that none is approaching the automation of road defect detection holistically. None is capable of addressing all limitations of current practice simultaneously. Although it is very useful to automate part of the process, a complete approach is what the industry is looking for. The reason is that information about all street related assets is necessary for efficient maintenance. So, even if an automated method focusing on one defect is applied, manual ways need to be applied as well to collect information for the rest. Thus, only a fully automated low-cost complete approach would be appealing to practitioners. The aforementioned findings constitute the contribution of this paper, which aimed at identifying the issues of current practice and limitations of current research on road defect detection.

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