Hyperspectral Imaging for Autonomous Inspection of Roads Pavement Defects

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Abstract -

Autonomous inspection of roads is gaining interest to improve the efficiency of road repair and maintenance. In this paper we will be showing the potential for using Hyper Spectral Cameras, HSC, to identify road defects. The key idea of this paper is that cracks in the road show the interior material of road pavement which have different chemical composition from the surface materials due to surface wear. Material changes of the road surface give rise to a spectral signature that can be easily detected in HSC images. This condition facilitates the detection of cracks and potholes, which can be difficult if working in the visible spectrum domain only. We report on experiments with a HSC to identify the road material changes and their association to cracks and potholes. A new metric is devised to measure the amount of metal oxides and associate its absence to the appearance of cracks. The metric is shown to be more discriminative than previous indicators in the literature.

Keywords -

Road crack detection; Pavement defect inspection; Hyperspectral Imaging; Autonomous road inspection.

1 Introduction

Detection of road cracks from images is difficult since cracks are dark, only have few features and hard to distinguish from road texture [1]. As a result, state of art road crack detection systems suffer from low recall and high false positive rates as reported by [2] [3]. Hyper Spectral Cameras, HSC, are considered in this paper in search for more discriminative clues for crack detection. HSC are used to measure typically spectral range of 350nm-2500nm which contains spectra beyond the human vision range (400nm-700nm). Hyperspectral imaging, though relatively expensive and developed mainly for satellite and scientific imaging, is now becoming affordable and can be exploited for city road monitoring. HSC can be used to identify changes of surface materials if it has a unique spectral signature. Our interest is to exploit HSC fitted on drones for road and infrastructure surface inspection to detect cracks and anomalies.

Hyperspectral imaging, HSI, has been used previously to classify road conditions from satellite images [4] [5] [6] [7] [8]. The research was intended to classify road conditions in general and the spatial resolution can not detect road cracks or defects. Only few papers considered the detection of pavement cracks based on hyperspectral data [1] [9] [10] . In such case HSC were fitted on drones of low altitude flights to have higher spatial resolutions to enable observing cracks. The previous studies considered using descriptors of the spectrum such as the VIS2 (intensity difference between 830nm and 490nm-showing metal oxide content) and Short Wave Infra Red, SWIR (Intensity difference between 2120nm and 2340 showing hydrocarbon content). The metrics measure the rise and decay of spectral response curve at the wavelength regions for metal oxides and hydrocarbon which usually characterizes road conditions. These metrics have also been linked [11] to the Pavement Condition Index, PCI,(A standard metric by ASTM D6433 and D5340, used to indicate the condition of road pavement and ranges 0-100) and is usually computed using visual surveys [5].

In this paper, a new spectral descriptor is proposed to describe the spectra of road pavement and, in particular, assist the search for cracks. New roads are mainly composed from minerals and hydrocarbons, while deteriorated roads show more metal oxides on their surfaces [5]. The regions sensitive to both metal oxides and minerals are shown in Figure 1. The hypothesis of this paper is that cracks have a different chemical composition as shown schematically in Figure 2 and therefore, present a unique spectral response. That response can be used to distinguish cracks from normal road surface material. A novel metric is proposed to measure the content of metal oxides from the spectra and associate its depletion to the appearance of road anomalies or cracks.

This paper is structured as follows: The next section outlines the relevant work in road condition analysis using hyper-spectral imaging, then, the new algorithm is described in detail in section 3. The experiments and results on real road conditions are described and discussed in section 4, whilst conclusions are drawn in section 5.

2 Related Work

Hyper-Spectral Imaging, HSI has been used in space and satellite cameras for remote sensing and analysis of natural resources and several other forestry and agricultural applications [12]. Some applications have used HSI as a tool for detecting forgery in art work [13]. It have also been used for art work authentication and for crack detection in paintings [14]. There is currently an increasing interest in the application of HSC with UAV to monitor the conditions of city roads, see [12] for a review of UAV based sensors. A simple UAV system was described in [15] for application in forestry and agriculture.

Several basic problems are still inherent in the use of HSI and infra red imagery. One is the need to measure the illumination colour, online rather than with a single measurement before using the sensor as is the current practise [16]. Another basic problem is blurred edges [12], since it severely affect the measurements due to spectral aberrations on edges and several studies have focused on de-blurring edges [17] [18].

Spectral mixing also occurs since one pixel of a satellite camera may represent more than five metres of different materials on earth. Hyperspectral un-mixing is useful for satellite images since it can improve the resolution and show different material contents. This effect is less significant when the camera is used at close range to surfaces. Hyperspectral images have been processed by super-resolution systems through different successful methods and reported to improve the spatial detection of target in typical 4 m resolution satellite images. [19] However, the issue of compromise between the spatial and spectral scale in hyperspectral imaging is critical and was the subject of extensive research in remote sensing [6] [20]. Table 1 summarizes the major works in the literature and their significant features. The table shows three categories of research namely: basic problems, physics-based solutions and pure learning approaches.

2.1 Physics-based approaches

Several spectral descriptors were developed in spectral and spatial domains for the classification and object detection in hyperspectral images [9] [18] [20] [21] . Approaches to associate the spectra of roads monitored from satellite with road conditions in general (not for crack detection) have been reported in [4] [10] . The simplest spectral descriptors were devised to measure the rise and decay of spectral response curves for road materials in the full spectral range of typical HSC that is (400nm-2500nm). The spectral descriptors are known as VIS2 and SWIR ratios [10]. The ratios were used as metrics for a material with the following definition [8]:

$$VIS2_{Difference} = I_{\lambda=830nm} - I_{\lambda=490nm} \tag{1}$$

$$VIS2_{Ratio} = \frac{I_{\lambda=830nm}}{I_{\lambda=490nm}} \tag{2}$$

where I is the intensity of light and (λ)is the wavelength in nano-metre, nm. The ratio SWIR is defined as:

$$SWIR = I_{\lambda=2120nm} - I_{\lambda=2340nm} \tag{3}$$

It should be noted that the metric VIS2 is termed as a ratio in the literature, while it is mathematically a difference. Therefore, we preferred to define it as two metrics, namely the difference and the ratio.

The frequency domain has been exploited to derive spectral metrics. A spectral similarity measure was suggested [22] using the magnitude values of the first few low-frequency components for spectral signature. Harmonic analysis was also used to describe the spectral reflectance and recognize objects [23].

The design of a spectral descriptor requires a compromise between accuracy and simplicity. It seems that a precise descriptor is required, which is easy to compute and encapsulates all the precious information obtained from the camera spectra. This was highlighted in [6] where they discussed whether Hyperspectral imaging with huge number of spectral bands is really required rather than using a limited number of bands, in a multi-spectral imaging fashion, at a much reduced cost.

2.2 Pure learning approaches

Deep learning and convolutional neural networks have been used in a purely learning approach to identify features in both spectral and spatial domains. Classification from a training set, such as the work reported by [24] [25]. The work in this category is interesting, especially for unsupervised classification, since there is a limited set of labelled data for training in general. It is also challenging due to the huge computational complexity of deep learning added to the complexity of the spectral cube typical for HSI [26]. Feature mining had also been reported to learn discriminative features from datasets through feature selection and reduction methods [27].

Table 1: Summary of Relevant Work

Category	Authors	Description	Resolution
Basic	Li et al [17]	Deblurring and spectral segmentation for material identification	3.7m
Basic	Lanaras et al. [20]	Study of hyperspectral super resolution problem	3.7m
Basic	Khan et al.[16]	Illuminant estimation in Multispectral imaging	3.7m
Basic	Simoes et al.[19]	A formula for Hyperspectral image super resolution to improve spatial detection of satellite images	3.7 m
Physics-Based	Jengo et al. [9]	Road condition assessment and detecting potholes. Used VIS2 and SWIR ratios as indicators.	0.5 m
Physics-Based	Herold et al. [5]	Road condition mapping using UAV and report good correlation between VIS2 ratio and PCI	1m
Physics-Based	Noronha et al. [6]	Road extraction and pavement condition evaluation from HSI, Recommended using fewer bands for efficient discrimination	2.5- 4.0 m
Physics-Based	Mohammadi [8]	Road classification using several spectral description functions	4m
Physics-Based	Wang et al. [22]	Frequency analysis for HSI clasification and proposed spectral similarity measure as a spectral indicator	3.7m
Physics-Based	Khuwuthyakorn et al. [23]	used harmonic analysis for spectral affine invariant descriptor for HSI	3.7m
Physics-Based	Carmon et al.[4]	Map road skid resistance (friction) to spectrum indicators and mentioned problem of atmospheric correction	1m
Physics-Based	Liang [7]	Detailed study of spectral spatial feature extraction for HSI image classification	3.7m
Pure Learning	Gao et al. [24]	HSI classification using CNN + Multiple feature learning for better class labelling	3.7m
Pure Learning	Liu et al. [25]	Active Deep learning classification in HSI using weighted incremental dictionary algorithm	3.7m
Pure Learning	Zhao, W. and Du, S. [26]	Deep learning approach for dimensional reduction and feature extraction for classification	3.7m

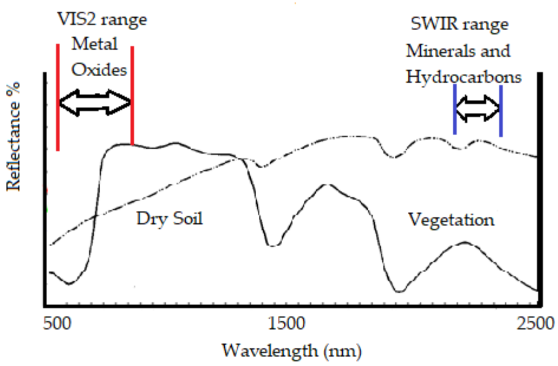

Figure 1: Spectral response and regions for describing pavements.

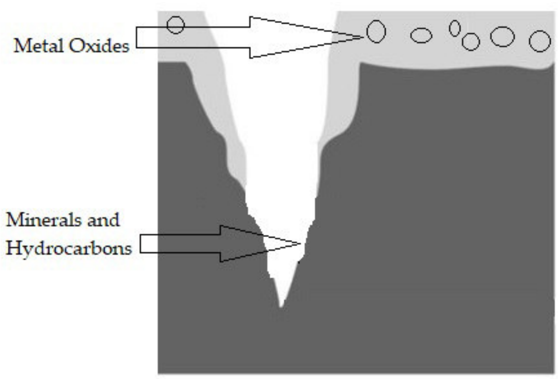

Figure 2: Schematic diagram showing the cross sectional view in a road pavement crack.

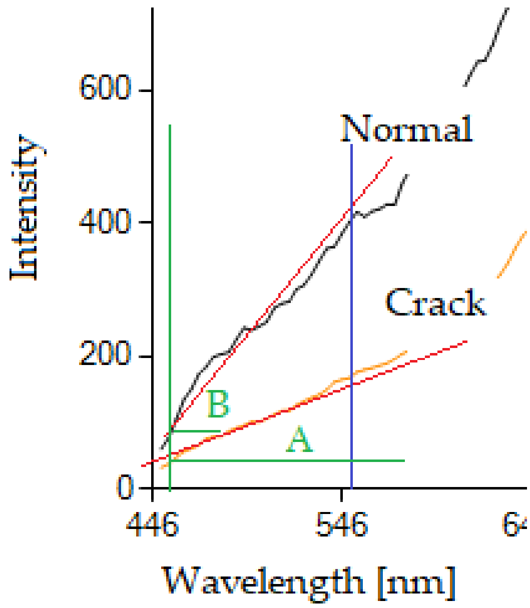

Figure 3: Method of computing the angle ϕ from spectral response.

3 The New Descriptor

A typical response curve from HSC is shown in Figure 1; the camera used is working in the Visible and Near Infra Red, VNIR spectral range. That means the spectral range that can be of interest for road material change detection, and hence cracks, is the range showing metal and iron oxide in particular. The response in the VNIR range changes significantly for road based on age and wear as reported in several studies (e.g., [6] [8] [28]).

The main idea is explained schematically in Figure 2. The crack shows the internal pavement material which is different in composition from the road surface due to surface wear. The surface usually reflects light similar to metal oxides because of gravel pigments and loss of the bonding asphalt rich in hydrocarbon and oil.

In the previous work, only the intensity at two spectral bands was used to derive the VIS2 ratio. The new descriptor relies on the observation from Figure 3, that the slope is different between cracks and normal surfaces in the range 450-550nm. In this paper, the approximate line that represents the spectrum in the region between 450nm and 550nm is found. The slope, S, of a line is computed using the least squares method in the range [450nm - 550nm]. The angle of the line from the horizontal axis is then found through the following equation:

$$\phi = \arctan(S) \tag{4}$$

The reason to select the range (450nm-550nm) is that it is representing the change of metal oxides in response. It is observed in Figure 4 of the spectral response that this particular region is almost straight without curves. This justification is proved empirically through the experiments.

There is an assumption that the surfaces are clean because the spectral response depends on the surface condition. Fortunately, the weather in the UK is often rainy, which increases the probability that road surfaces will be clean from dust and other metal oxides that may impair the crack detection.

The application for road inspection also requires low sensitivity to illumination colour because in real outdoor situations, the illumination colour will continually change. This issue will not be covered here and we will rely on measuring the illumination with the standard grey patch before measurement with the assumption that illumination is not changing after the calibration.

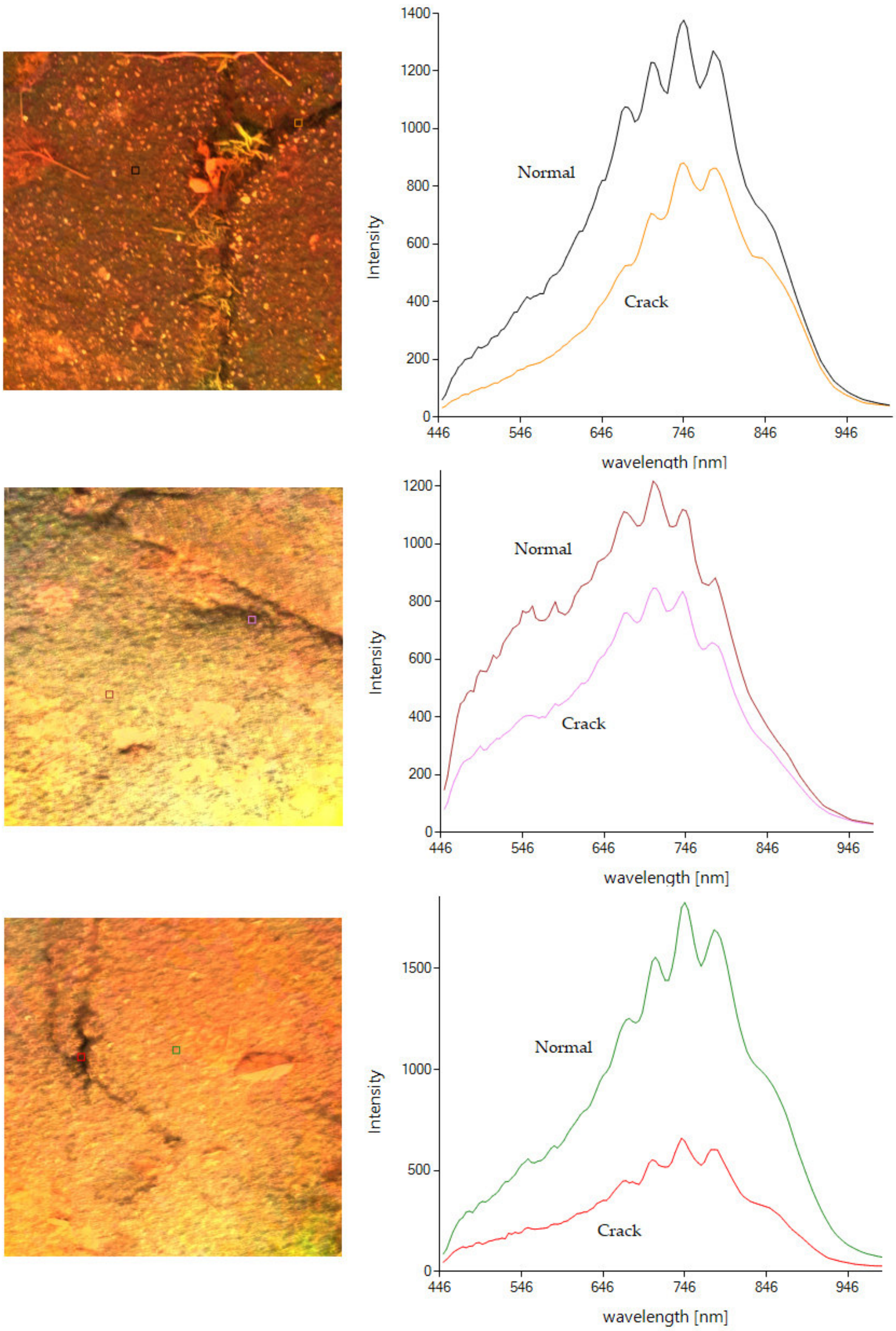

Figure 4: Sample HSC images of pavements (left) and their spectral characteristics (right) inside the regions marked by coloured squares in the HSC images.

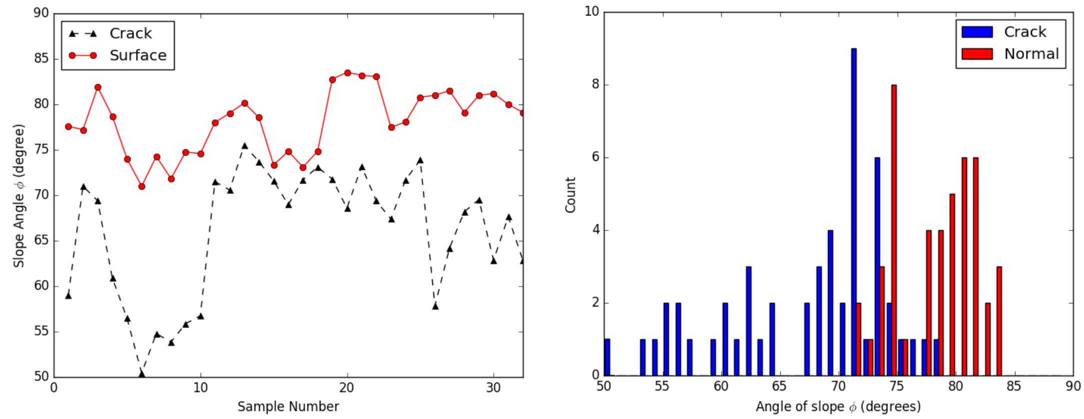

Figure 5: Proposed slope angle ϕ (Left) computed for Sample Pavement for crack and surface regions, and the histogram (Right)

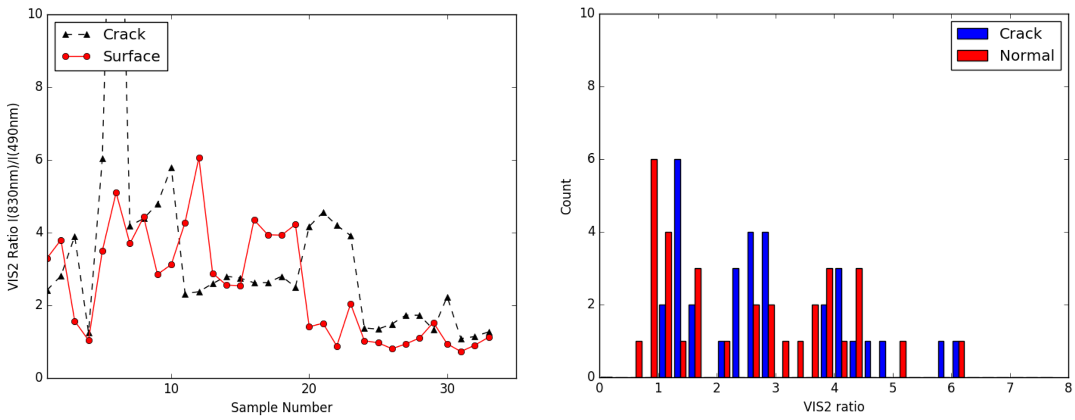

Figure 6: VIS2 Ratio (Left) computed for Sample Pavement for crack and surface regions and the histogram (Right)

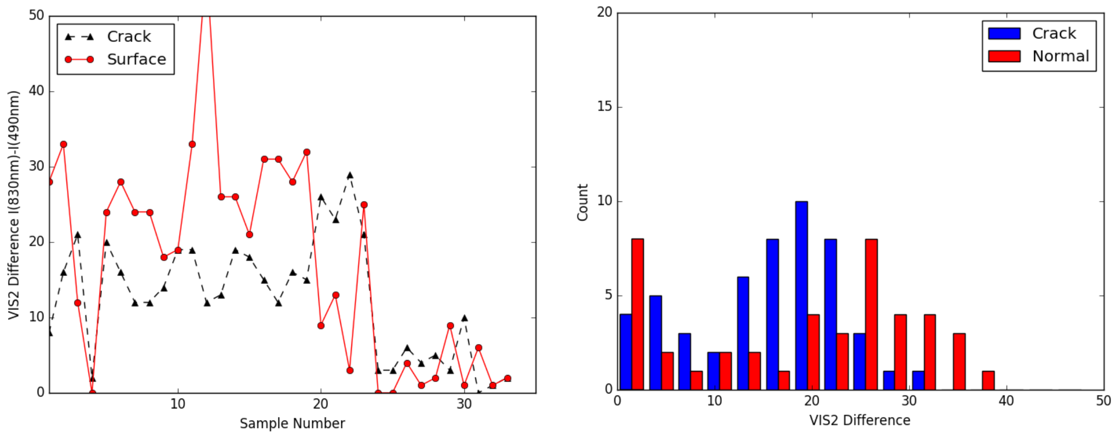

Figure 7: VIS2 Difference (Left) computed for Sample Pavement for crack and surface regions and the histogram (Right)

4 Results

The hyperspectral camera used in this study is a Cubert (model S185) measuring in the range (450nm-950nm) across 125 channels and fitted with a lens of 23 mm focal length. The total image size is 1000*1000 pixels. With the optical system used, one pixel represent (0.5 * 0.5) mm area at one metre depth. The spectral range of the camera enables the measurement of the metal oxides's sensitive spectra as shown in Figure 1.

Several experiments were conducted using the camera to view real cracks in paved roads and 3 sample results are shown in Figure 4. The location of cracks are known in these experiments and both 'normal surface' and 'crack' pixels were randomly selected from identified areas. The images are shown on the left-hand side of Figure 4 and two square windows marked in the image, one for normal road surface and another for a crack region. The right-hand side curve shows the spectral response of both normal surface and crack reflection. The area used to capture the spectrum is fixed during this experiment to one pixel size.
It can be observed in Figure 4, that the crack reflection is less than the reflection from normal surface. It can also be observed that the slope of the spectrum in 450nm-550nm range is radically different from normal to crack surfaces. The angle ϕ was computed using Equation 4, and shown in Figure 5 for regions of both cracks and normal surfaces for comparison.

It can be observed that the slope angle is lower for the crack regions than the surface regions of the pavements in most of the cases. The histograms of this angle computed for cracks and normal surfaces have very little overlap as shown in the right-hand side of Figure 5. However, for any given sample, the angle of slope of crack is always lower than that of road surface. This implies that a single threshold can be used to discriminate cracks from normal surfaces.

The VIS2 ratio was computed for the same sample set and is shown in Figure 6 as a ratio (Equation 2). The VIS2 difference (Equation 1) is also computed and shown in Figure 7. It is observed that the histograms are almost 80 % overlapping in Figures 6 and 7 compared to less than 20 % overlap in Figure 5.

5 Conclusions

Hyperspectral imaging is exploited in this paper to discover the defects and anomalies in road pavement. HSC has the potential to be useful for revealing the defects in infrastructure by observing the changes in spectral reflectance caused by different materials. A new metric was used in this study as an indicator for the change of material and was shown to be a good indicator representing the change of metal oxides in the spectral region 450nm-550nm. The angle of slope of the spectral line in this region, is shown to be better than the VIS2 metric. The angle of the slope utilizes more information from the spectral response than the previous VIS2 indicator. Exploiting more spectral information is good to improve the clues used to find material changes and hence associate this with cracks and potholes and even normal wear of the road surface. This finding may allow fast extraction of defective road pavement areas.

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