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Automatic Road Survey by Using Vehicle Mounted Laser for Road Asset Management

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ABSTRACT In most countries local roads (i.e., urban and rural) form over 80% of the entire road network and constitute the country's largest asset value. In order for local roads to remain fit for purpose and maintain their value, they require periodic maintenance. To make the best use of scarce maintenance resources, road maintenance needs to be preventative which requires the condition of the road to be assessed periodically. Traditional road surveys suffer from the lack of repeatability and reproducibility, are high cost and time consuming. This work proposes a vehicle mounted point laser system for the automated, rapid and inexpensive measurement of a major mode of local road deterioration, namely fretting. Compared to other technologies such as Ground Penetrating Radar (GPR), visual sensors and the Mobile Laser Scanning (MLS) system, the point laser requires less computational power, is less sensitive to the surrounding environment and is of comparatively low cost. A robust approach is proposed which consists of a number of pre-processing algorithms to deal with noise and the effects of the vehicles dynamic motion, and a signal processing algorithm which analyses histograms of the distance from the road surface measured by the laser to account for changes in road texture. Road fretting measured by the proposed system on a variety of roads is compared with fretting determined using a standard visual assessment process. The results indicate that the proposed system can measure road fretting to the levels of detail which are suitable for planning, programming and preparations road management functions.

INDEX TERMS Point laser, histogram analysis, road survey, fretting, road asset management.

I. INTRODUCTION

The benefits of well-maintained road networks in terms of economic and social development have been recognised for many years [1]. However, due to the combined effects of traffic and the environment roads deteriorate over time necessitating their maintenance [2]. Applying preventative road maintenance at an early stage of a road's deterioration has been found to be 6-10 times less expensive than waiting until the road requires rehabilitation [3]. Furthermore, road use costs (i.e. vehicle fuel, maintenance, travel time, accident and environment costs) reduce as road condition improves. Therefore, to enable a road asset manager to make best use of resources, the condition of a road network needs to be assessed periodically so that the road maintenance can be applied timely and appropriately.

Road networks are extensive, and their assessment is both time consuming and costly and research has been ongoing for many years to develop automated tools for road condition assessment. These include sophisticated instrumented vehicles travelling at normal traffic speeds to assess road functional and structural conditions [4]–[6]. Most of these technologies have been developed for the assessment of strategic road networks whose deterioration is driven by the damage caused by vehicular traffic. Further, because of the high volume of traffic using these roads, much of the focus has been on the measurement of road roughness which is directly related to road use costs. Less attention has been given to the development of technologies for local roads (i.e., urban and rural roads), which typically make up more than 80% of a country's road network [1]. Local road networks are built to lower standards than strategic roads, carry much lower levels of traffic and therefore their deterioration is due primarily to the environment and therefore the assessment of road roughness is arguably less important than

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for strategic road networks. The primary modes of deterioration of surfaced local roads tend to be cracking and fretting (surface disintegration leading to the formation of potholes). The early detection of cracking and fretting allows for timely and cost-effective preventative maintenance [7]. The non-homogeneity of the roads within a local road network in terms of age, amounts of deterioration and surface texture make the automated assessment of cracking and fretting challenging. This is compounded during a survey due to a variability in illumination and surface moisture. Consequently, evaluation of the local road is often by visual surveys [8]. These types of surveys can however be subject to a lack of repeatability and reproducibility, are costly and time consuming and have safety implications [8]. Advances in in sensor technologies, computing power and data transmission and development of computational algorithms offer the potential for fast reliable, accurate and in-expensive automated local road surveys at traffic speeds in real-time [7].

A number of automated systems for capturing road surface information are described in the literature. These include systems using video [9], smartphones [10], Ground Penetrating Radar (GPR) [11], and laser technologies for road information inventory [12] and road marking recognition [4]. In this work, a point laser system fitted to a moving vehicle is used to capture road surface information. The collected raw data is analysed to identify road surface fretting. The methodology includes pre-processing to remove signal noise comprising an adaptive thresholding technique for sensor noise removal and a baseline correction to account for vehicle dynamic motion. Afterwards, a global-local histogram analysis technique is used to determine two features from which road surface fretting is estimated. The proposed system focuses on network level road condition assessment, it is verified by using visual inspection data collected from a number of different road surface types. The experimental results from the real survey demonstrate the feasibility of the proposed concepts.

The paper is organized as follows, Section II outlines the state-of-the-art of road condition survey technologies; Section III describes the proposed system and datasets used; Section IV presents the signal processing and histogram analysis processes; Section V analyses the experimental results; conclusions are given in Section VI.

II. RELATED WORK

This section reviews the feasibility of various approaches for road condition assessment that couple sensor technologies with computational algorithms.

A. ROAD SURVEY SYSTEM

Several types of sensor technologies are described in the literature for road condition surveys. These can be categorised as: a) mechanical wave, 2) electromagnetic wave and 3) image-based techniques.

The first category includes ultrasonic [13], [14] and acoustic [15], [16] based systems that transmit waves between 20 Hz to 20 MHz. These systems have shown a good ability to measure the condition of various types of infrastructure. For example, [13] implements a bicycle-mounted ultrasonic system to measure the road profile. Work by [15] uses an acoustic system to examine the thickness of the asphalt concrete layer of a road. However, the resolution of ultrasonic/acoustic systems is insufficient for the assessment of road cracking and fretting (less than 1 mm), and also water on the road surface and ambient temperature both affect the detection performance [14], [16].

Electromagnetic wave techniques include Ground Penetrating Radar (GPR) [11], [17], Light Detection And Ranging (LiDAR) [5], [12] and laser systems [4], [18], [19]. The GPR system has been widely used for monitoring the condition of buried infrastructure. For example, research described by [17] uses a high frequency GPR to detect transversal cracks and work by [11] assess the ability of a GPR system to detect longitudinal cracks on the road surface. The main limitation of GPR based systems is that the interpretation of results is generally non-intuitive and problematic and the procedure suffers from signal scattering under heterogeneous conditions (e.g. thickness of road surface). A LiDAR system fires rapid pulses at a surface and measures the amount of time it takes for each pulse to be reflected back [20]. The reflected signal is normally processed with point cloud techniques. A downward-looking LiDAR system has been developed by [5] to detect the boundaries of roads and obstacles and [12] presents the potential of LiDAR to record road inventory.

In the third category, visual systems have a wide range of resolutions that are capable of detecting large objects like obstacles on the road surface [21] and road markings [4] as well as small features such as cracking [9] and road surface texture [22]. Recent rapid developments in deep learning technologies have enabled visual based systems to achieve a high accuracy in terms of image classification and segmentation [9]. However, visual systems are limited by the illumination levels of the road surface constraining their use in inclement weather such as rain and snow and also under conditions where the road surface is partly occluded. Further, the requirement for large amounts of training data increases the cost for road surveys and potentially limits the application of these systems for the analysis of road networks where, during a survey, the environment can change rapidly, the types of defects vary considerably and the road surfaces can differ in terms of surface texture, colour and construction.

B. OTHER LASER-BASED SYSTEMS

Mobile laser scanning (MLS) systems provide a high-resolution measurement that generates a considerable data density in a relatively short time period. Normally, MLS data is processed as an image. The MLS system outlined by [18] measures the road surface in 3D and extracts longitudinal profile data to evaluate possible defects. The MLS system has also been used for identifying road markings [4] by examining the grey-level intensity of road features on the road surface and classifying these using a decision tree. A more advanced MLS system [20] takes the advantage of

geo-referenced features based to classify road surface texture, road markings and road cracking. Work by [6] uses a MLS system that incorporates machine learning based recognition to identify the road surface and surrounding objects including trees, vehicles and buildings. A more recent work [23] extracts transverse profiles and ruts of the road using point clouds acquired by a MLS system mounted on a specialized vehicle. However, the above MLS systems all have high complex signal processing that require significant computational power and therefore the data needs to be processed off-line. This introduces additional costs and limits their use for rapid large-scale road network surveys.

The point laser system in contrast to the MLS system does not scan the entire road surface but only takes measurements in the direction of travel i.e. longitudinally. Thereby, point laser systems can significantly reduce the amount of data captured. An evident disadvantage however of these systems is that a single point laser cannot provide transverse information thereby potentially reducing the accuracy of a survey compared to the MLS system. Research using point laser systems for the analysis of the condition of the road surface is ongoing. For example, [19] explored the use of a point laser for the automatic measurement of fretting of the road surface at traffic speeds. Work by [24] built on this approach by improving the signal processing algorithms suggested by [19] to incorporate an approach based on the Root-Mean-Square (RMS) value of the laser measurement. However, the dataset used by [24] was limited in extent, was obtained under a controlled environment and the noise, including that from vehicle dynamic motions was not considered. The use of a point laser approach to assess road maintenance requirements based on road texture measurement (specifically the sensor measured texture depth (SMTD)) and the mean profile depth (MPD)) is proposed by [25]. However, the approach was unable to distinguish between road texture and other road defects and did not include pre-processing to remove noise. Our previous work [26] has demonstrated the estimation of road fretting from a feature vector based on a peak detection algorithm. The system was shown to have comparable accuracy to a visual system but requires significant computational effort.

III. SYSTEM AND DATASET

A. HARRIS2 SYSTEM

The survey vehicle used in this work was developed by the Transportation Research Laboratory (TRL) Ltd, namely the Highways Agency Road Research Information System 2 (HARRIS2) [24]. HARRIS2 has five ProfiCura 2D point lasers [27] mounted on the front of a vehicle. A GPS antenna is attached on the top of the vehicle to provide road survey location reference information. The collected road condition data and GPS signal are synchronized and stored in an on-board computer for further analysis. An overview of HARRIS2 is shown in Fig 1.

Three resolutions, summarised on Table 1, of the point laser system are important to determine the system's ability

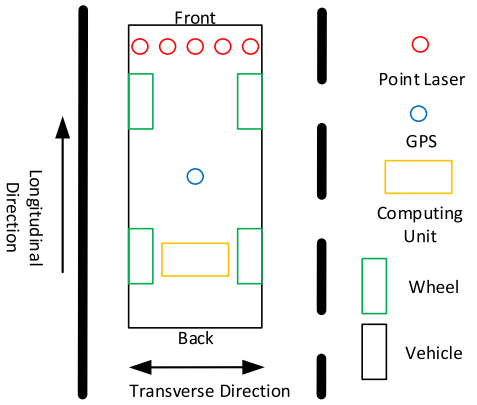

FIGURE 1. Overview of the HARRIS2.

TABLE 1. Parameters of point laser system.

	Formula	mm
Longitudinal Resolution	S_v/S_s	0.803
Transverse Resolution	$D_w/(N_L-1)$	$1.05*10^3$
Vertical Resolution	[27]	0.25

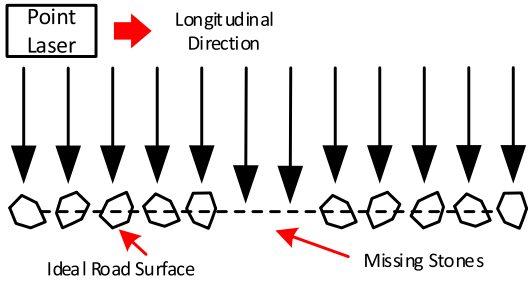

FIGURE 2. Principle of point laser.

to identify fretting. These are the longitudinal resolution (distance along the road direction between each adjacent laser measurement), the transverse resolution (horizontal spacing of the laser) and the vertical resolution (minimum measurable distance in the vertical direction). The longitudinal resolution is defined by the vehicle speed S_v and scanning rate S_s. In HARRIS2, the scanning rate is controlled by an Inertial Measurement Unit (IMU) to ensure that the rate remains constant during a survey. In this work, the longitudinal resolution was fixed at 0.803 mm which has been shown to be sufficient for the micro-texture of stone chips on the road surface to be measured [28]. The transverse resolution is defined by the scanning width D_w (4.2m for HARRIS2) and the number of point lasers (five in this work). For this work, the usefulness of the system is demonstrated using only the laser in the near wheel path (the left most laser in Fig 1), although it is recognized that using information from the other point lasers might improve the detection performance. The vertical resolution of the laser used in HARRIS2 is 0.25 mm [27] according to the specification.

B. PRINCIPLE OF POINT LASER

The principle of the point laser measurement to detect road fretting is idealised in Fig 2. A point laser is moving along

the longitudinal direction and fretting, in the form of missing stones (i.e., aggregate), is shown in the middle of the road section. The downward facing point laser transmits a laser beam towards the road surface and measures the Time-of-Flight (ToF) of the reflected beam. An ideal, smooth intact road surface would reflect the light from the laser homogeneously to the laser sensor. In reality, light in the deteriorated road section has a number of reflection paths back to the point laser sensor. Consequently, a number of irregular measurements are recorded compared to the measurement of the intact road surface. Therefore, it is possible to extract the area of fretting from an intact road surface based on the degree of evenness of the reflected signals.

However, the real situation is not as simple as this, as there are several sources of noise that can significantly affect the detection performance of a point laser system. These are:

- **Point laser errors:** These types of errors relate to the measurement of distance by the laser and are caused by the internal clock in the sensor providing abnormal measurements of the ToF between outward and inward laser pulses.
- **Vehicle dynamics:** The point laser measures the distance between the vehicle and road surface. However, the dynamic motions of the moving vehicle introduce significant interference in the vertical direction relative to the road surface. These motions can be far greater in magnitude than the depth of fretting thus making it problematic to distinguish the changes due to fretting and due to the vehicle's dynamic motion.
- **Texture type:** The road surface is textured by means of the addition of aggregates (stones) to increase surface skid resistance and allow for the removal of water thereby improving road safety. The aggregates are not uniformly shaped nor sized introducing local variations in the height of the road surface and thereby complicating the measurement of fretting (i.e., the disintegration of the road surface primarily caused by the loss of aggregates). This is exacerbated as rural road networks can be constructed from a variety of surface materials and aggregates depending on a number of factors. These include the speed, volume and type of traffic, the available finance for road construction and maintenance and environmental considerations such as noise reduction [29]. As a result during the survey of a road network, the ToF measured by a laser sensor varies along the surface of a road built from a single type of material because the aggregates on the road surface are non-uniform in shape, size and spacing (irrespective of the presence of any form of deterioration). Further, a road survey is more likely to encounter different types of road surfaces within the network which will also have different types, sizes and spacing of aggregates.

An example of the raw data from a point laser measurement of a road surface is shown in Fig 3. The data consists of the distance from the laser sensor to the road surface as the ordinate against the distance travelled along the road as the abscissa. As mentioned above, one measurement is made every 0.803 mm. Each measurement in Fig 3(a) is a combination of four elements: (1) road fretting as in Fig 3(b), (2) point laser error as in Fig 3(c), (3) vehicle dynamic motion Fig 3(d) and (4) road texture Fig 3(e). In order to obtain the correct road condition, the components other than that due to fretting need to be removed. For convenience, the magnitude y of the point laser data at time t can be written as a superposition of these components as given by Equation 1:

$$y(t) = y^F(t) + y^S(t) + y^V(t) + y^T(t) + n(t) \quad (1)$$

where y^F, y^S, y^V, y^T, n are road fretting, point laser error, vehicle dynamic, road texture and noise from other sources respectively.

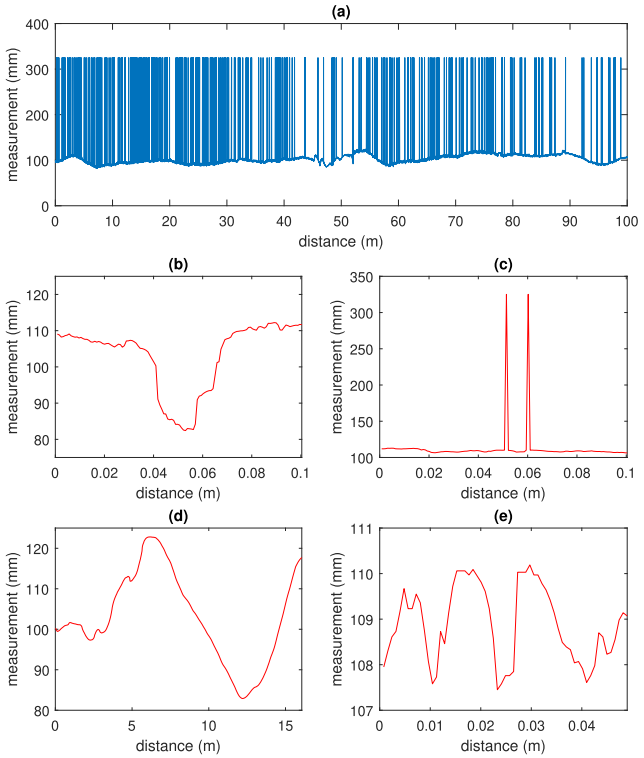

FIGURE 3. Data from the point laser, (a) raw data, (b) road fretting, (c) point laser error, (d) vehicle dynamic and (e) road texture.

TABLE 2. Details of the road survey.

Road	Description	Length	Class	Fretting Level
One	Byron Dr	0.421	Secondary Road	L
Two	Duke's ride	0.480	B Road	L
Three	Wokingham Rd	0.711	A Road	M
Four	Hanworth Rd	1.337	Secondary Road	H

C. DATASET FROM ROAD SURVEY

The road survey data was collected on local roads near Crowthorne, United Kingdom (longitude 0°47'31.88'' E, latitude 51°22'12.97'' N) using the HARRIS2 system. In order to better verify the concept for the point laser system, four roads in different conditions (Table 2) were surveyed with

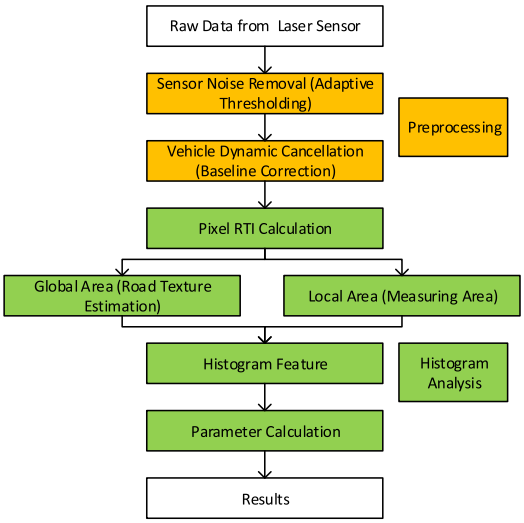

FIGURE 4. Overview of the proposed methodology.

Low (L), Low/Middle (LM), Middle (M) and High (H) fretting level. The four roads are busy routes which serve local communities, are used by tourists and provide through routes for freight traffic. According to the UK road classification system they are classified as an A Road (highest class of local road), B Road (second highest class of road), and Secondary Road (roads without numbers or unclassified roads) [30]. The survey was undertaken in dry conditions.

During the road survey, HARRIS2 was driven at normal speed of between 0 to 80 km/s, depending on the amount of traffic and the timing of traffic signals. An operator controlled the computing unit to start a survey and it stopped automatically at a predefined location. The collected data was stored and time-stamped. To evaluate the overall detection performance of the proposed approach, the amount of fretting on each of the roads was also determined using the detailed visual inspection windshield survey approach specified in UK standards [31].

IV. PROPOSED METHODOLOGY

In this work, a robust methodology for assessing the road condition including a pre-processing and histogram analysis is proposed. The pre-processing includes an adaptive thresholding technique to identify and remove the noise and a baseline correction to cancel the vehicle dynamic motion. The histogram analysis includes a pixel calculation as representative of the laser measurement and a global-local area comparison for road texture estimation. Afterwards, two histogram features are calculated to present the road condition. An overview of the flow chart of the proposed methodology is shown in the flow chart in Fig 4.

A. SENSOR NOISE REMOVAL

As mentioned above, a major source of noise is due to the sensor. By analysing the dataset from all four roads, this type of error accounts for 0.5% of all data points. As the

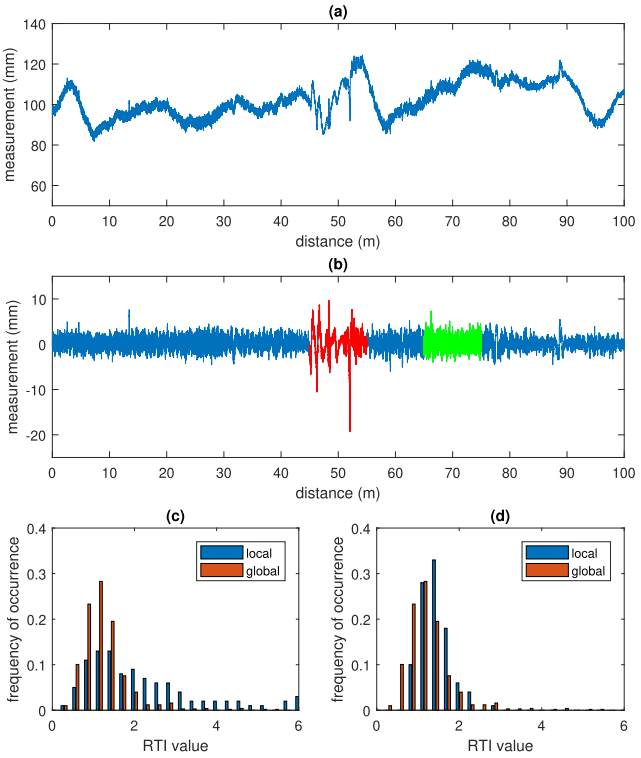

FIGURE 5. An example of proposed methodology, (a) with sensor noise removal, (b) with dynamic motion removal, (c) histogram analysis for road 45-55m (red part) and (d) histogram analysis for road 65-75m (green part).

longitudinal resolution of the data is 0.803 mm, there are approximately six errors per metre. If not removed, these abnormal measurements could affect the performance of the later histogram analysis.

In this work, a two-step algorithm has been developed to detect and remove the erroneous data points whilst keeping the other authentic data points. Firstly, an adaptive threshold value $T(t)$ is generated to identify the outlying data points based on a moving average method. The adaptive threshold is calculated using Equation 2:

$$T(t) = \sum_{i=-\frac{1}{2}l_s}^{\frac{1}{2}l_s} c_i y(t+i) + w \tag{2}$$

where l_s is the window length for point laser error y^S, the weight is defined as $c_i = 1/(l_s + 1)$, and w is a constant for the thresholding purpose.

The second step is to replace the erroneous data with values above $T(t)$ with estimated values. This is achieved by calculating the mean value of adjacent authentic data points. The mean value, y_i^S is calculated using Equation 3:

$$y_i^S = \frac{1}{2n}(y_{i-n} + \ldots + y_{i+n}) \tag{3}$$

where all data points from y_{i-n} to y_{i+n} are authentic measurements. For the dataset, n was set, following a trial and error process, to be equal to 10. Based on the example data shown in Fig 3(a), the resulting data is shown in Fig 5(a). As can

be seen, all erroneous data from y^S has been successfully detected and replaced.

B. REMOVAL OF VEHICLE DYNAMIC MOTION

As discussed before, vehicle dynamic motions can have a significant impact on measuring road fretting. For the current dataset, the dynamic motion of the data collection vehicle can result in perturbations of more than ±20 mm as shown in Fig 3(d). The duration and frequency of the vehicle dynamic motions are not constant and vary according to a number of factors including the vehicle speed and the road surface condition. The effect from vehicle dynamics y^V can be considered as a baseline correction problem since it has significantly greater fluctuations in terms of magnitude and duration than the components of the dataset [32]. Considering the algorithm complexity and processing speed, the Moving Average of Minima (MAM) technique, which shares a similar structure to the moving average technique, was chosen.

The first step is to estimate the baseline $\dot{y}^V(t)$ by using Equation 2, without the w constant, and to apply a window length for the vehicle dynamic l_v. An empirical trial and error process was used to determine the length of l_v. From this the most appropriate value of l_v was found to be five metres as this length ensured that the road surface information is not removed while minimizing the effect of the vehicle dynamic motion. The second step is to subtract this estimated baseline using Equation 4:

$$\hat{y}(t) = y(t) - \dot{y}^V(t) \tag{4}$$

where $\hat{y}(t)$ represents the data points after the removal of the vehicle dynamics. The corresponding results for Fig 5(a) is shown in Fig 5(b). The effect of applying the baseline correction process on the dataset shown in Fig 3(a) is given in Fig 5(b). It can be seen that the major component due to the vehicle dynamic motion has been removed and that the road surface information is clearly presented. After the pre-processing stage, the data points are a combination of road fretting y^F and road texture y^T.

C. PIXEL RTI CALCULATION

Research reported in the literature for the analysis of data captured by lasers to detect road surface defects [4], [20], [33] required computationally intensive processes, for example, feature decomposition and pattern recognition. In this paper, a low complexity method for disintegrating the road surface is proposed.

In our previous work [34], an index known as Root Texture Index (RTI) was defined. RTI calculates the Root-Mean-Square (RMS) value of the noise corrected laser data for a given length of road surface (or number of laser measurements). In this research, this length of road surface is referred to as a pixel and the RTI value can thus be considered as a measure of the average magnitude of the measurements within a pixel. The RTI value is calculated using Equation 5:

$$RTI_i = \sqrt{\frac{1}{l_p}\sum_{t=0}^{l_p-1} y(t)^2} \tag{5}$$

where l_p is the number of data points of each pixel.

D. GLOBAL-LOCAL DEFINITION

The RTI value of a pixel cannot be used directly to determine surface deterioration because, as mentioned above, variations in the measurements made by the laser signal will occur due to the presence of aggregates in the road surface (i.e., the road texture). Further, during an automated traffic-speed road survey, it is impractical for the operator to manually input information about the road texture type and therefore a process is needed that can determine the fretting on the road surface without any knowledge of the texture of the road (i.e. road surface type). To achieve this, following [24] the RTI pixel values of the pixels within small lengths of the road surface (local lengths) were calculated and compared to the RTI pixel values for a large length (global length). If a large enough global length is chosen, relative to any defects which may be apparent on the road surface, then the RTI pixel values of the global length will, in general, represent variations in measurement due to the road texture. If the smaller local length is of sufficient size, then its RTI values will in general reflect the presence of the road surface deterioration (i.e., fretting) in that length of road. Thus, variations can be distinguished between road profile due to the occurrence of surface defects such as fretting (i.e., that present in the local area) and those due only to the texture of the road surface (i.e., that obtained from the global area). The relationship between the global length l_g, local length l_l and pixel length l_p is $l_g > l_l \gg l_p$.

An example of two pairs of frequency histograms of the local and global measurements are provided in Fig 5(c) and (d). These have been determined from the laser point data obtained from sections 45-55m and 65-75m respectively of the road shown in Fig 5(b). The measurements for the 45-55m section show much greater fluctuations than those for the 65-75m section, indicating significant areas of road deterioration in the first section but not the second. This is reflected by the corresponding histograms. The histogram from the local length in the first road section shows a higher frequency of occurrence of high valued RTI pixel values than the histogram representing the global length. On the other hand, the frequency histograms of RTI pixel values for the second road section are similar.

E. HISTOGRAM FEATURES

Histogram features have been used to automatically determine the difference/similarity of the histograms of local and global RTI pixel values, and thereby the presence of fretting. Let the histogram feature of the global area be represented as h_g and the local area as h_l, respectively. Two parameters were adopted as follows:

- Mean-Square-Error (MSE). MSE represents the difference between the RTI distribution of the local and surrounding global lengths. A low MSE value occurs if the distributions of local and global RTI values are similar and thus there is a low amount of fretting in the local length. MSE is calculated as $MSE = \frac{1}{n}\sum_{i=0}^{n}\left|h_{g_i} - h_{l_i}\right|$.
- Correlation-coefficient (R). R is a measure of the similarity between the frequency distribution of the RTI values of the local length and that of the global length. Low R values indicate that the local RTI distribution is significantly different to the global RTI distribution and therefore the local length of road contains large amounts of fretting. R is calculated as $R = \frac{\sum_{i=0}^{n} h_{g_i} h_{l_i}}{n\sigma_{h_g}\sigma_{h_l}}$, where σ represents the standard deviation.

V. EXPERIMENTAL RESULTS AND DISCUSSIONS

In this section, the accuracy of the proposed system for road asset management using the dataset described in Section III C is demonstrated. The performance of the methodology is compared to the detailed visual inspection (DVI) survey method used to asses the condition of the UK's local road network [31]. The DVI data measures the fretting area (in square metres) for each 20 m^2 area of the surveyed road (both the longitudinal and transverse directions are taken into account). The proposed system measures fretting in the longitudinal direction only and therefore it might be expected that the results determined by the proposed system may not closely match that determined by the DVI methodology. However, in the majority of cases fretting initially forms in the vehicle wheel path. As the road surface ages environmental induced deterioration causes fretting to extend across the width of the road to the un-trafficked areas. As the ages of the surfaces of the roads chosen for this survey are relatively young, the fretting in the wheel path would be expected to be a reasonable representation of fretting across the entire road surface.

A. RATIO BETWEEN GLOBAL AND LOCAL LENGTH

As mentioned above, the selection of appropriate global and-local lengths is important for taking into account road texture. If the global length is not long enough, then the effect of road texture may not be taken into account sufficiently. However, if the global length is too long, then changes in texture resulting from the road surface during a survey may not be apparent and additional unnecessary computational processing time will be required. Thus, it is important to determine the optimal ratio between the global and local length. To determine the most appropriate ratio for the roads analysed, the local length l_l was set as 20m to replicate the DVI methodology and a number of global lengths lg between 40 to 400m were trialled. The average MSE and R values plotted against the ratio of global/local are shown in Fig 6. As can be seen, the MSE values increase with the global/local ratio until the ratio reaches 10 and is constant thereafter, whereas the R values show the opposite.

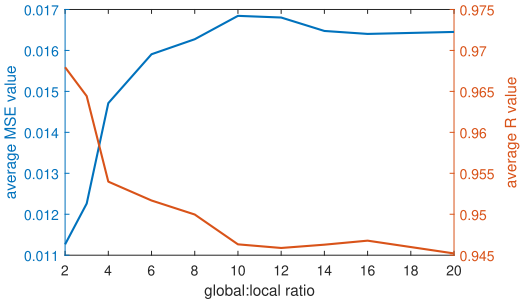

FIGURE 6. Detection performance versus the global-local ratio.

Therefore, a $l_l : l_g$ ratio of 10 was selected and as the local length has been set at 20 m, a global length of 200m was used.

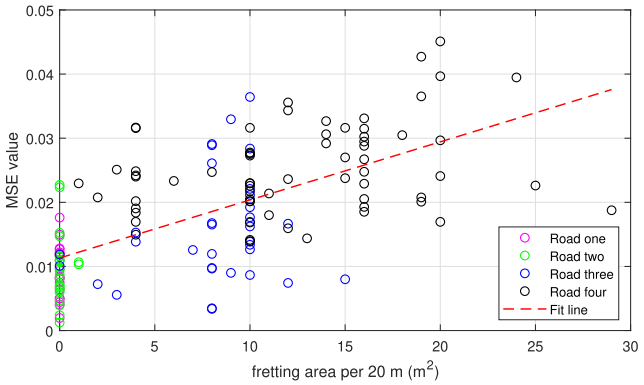

FIGURE 7. Scatter plot of MSE values vs. DVI fretting.

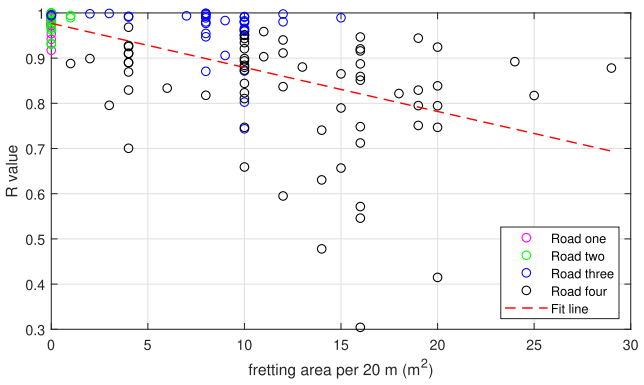

FIGURE 8. Scatter plot of R values vs. DVI Fretting.

B. COMPARISON WITH GROUND TRUTH

Figs 7 and 8 show the MSE and R values determined for each local length of road against the visual survey DVI data for all four roads. A straight line has been drawn through the data points in both figures using a linear regression polynomial function. In general, the results demonstrate that, as the MSE value calculated for a local length of road increases, the DVI determined fretting increases. Conversely, in general there is an inverse relationship between the R value and the DVI determined results. It is apparent from the dataset that most

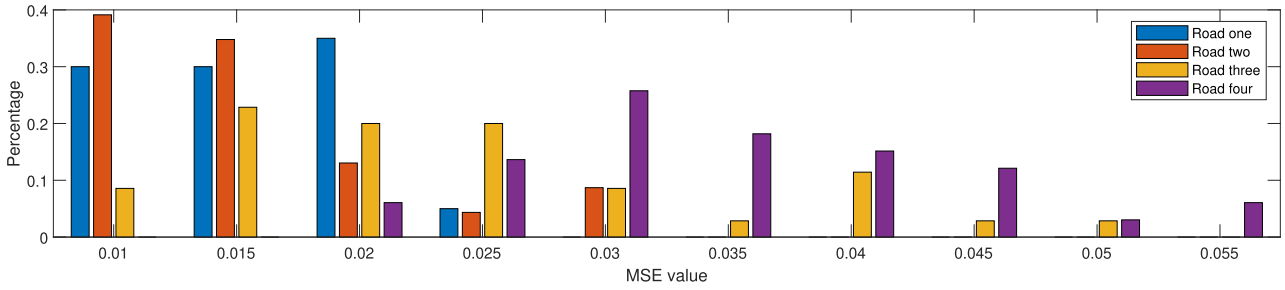

FIGURE 9. MSE values of four road surveys.

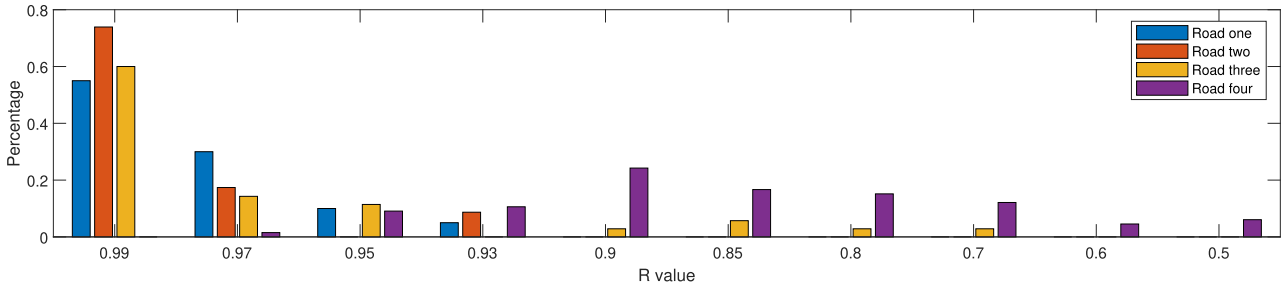

FIGURE 10. R values of four road surveys.

of the fretting is in the very low to medium range (DVI values of between $0 - 20\ m^2$ and there is little data showing high amounts of fretting ($> 20m^2$ and thus more data is required) to accurately verify the relationship.

It is apparent that the proposed methodology can separate road sections with low levels of fretting (roads one and two) and those roads with higher levels of fretting (most sections of roads three and four). In general, the MSE values in roads one and two fluctuate less than roads three and four. Further, the sections of the roads in all four figures with low levels of fretting have lower MSE values than those with high levels of fretting. Similarly, the R values for the roads with low levels of fretting fluctuate less than for the other two roads and the sections of road with low amounts of fretting have higher R values.

The MSE and R values shown in Figs 7 and 8 are presented in Figs 9 and 10 in the form of histograms of the normalised frequency of occurrence. The histograms show clearly the condition of each road. MSE values for both roads one and two are in the range between 0.01 and 0.02 and the large majority of their R values are between 0.99 and 0.97. This suggests both roads are on the whole in good condition and correspond to their actual road condition indicated in Table 2. In comparison, the majority of the MSE values of road four are between 0.03 and 0.04, and the majority of R values of the road is less then 0.90. This suggests that the road is in poor condition and corresponds to the road's actual condition shown in Table 1. Similarly, the MSE and R values of road three indicate that it is in worse condition than roads one and two but in better condition than road four. This finding is verified by the actual condition of the road given in Table 2.

It is evident from Figs 7-10 that there are some differences between the values of fretting determined by the visually collected data and those computed by the proposed system, especially where there are very high amounts of fretting. There are a number of possible reasons for the differences between the fretting determined by the proposed system and the visual based DVI data. Firstly, a distinct change in the average texture depth of a road (e.g. due to a change in road surface type) within a length of road equal to the global length will result in the global histogram representing more than one road surface type. Errors in fretting detection may occur where this change causes the frequency histogram of the global length to change markedly. Secondly, the point laser scans only the longitudinal direction of the road surface in the left wheel path whereas the DVI survey assesses the whole area of the road. Moreover, as discussed before, the dynamic motion of the data collection vehicle dynamic can have a significant effect on the point laser measurement system, and the single MAM filter suggested may not be sufficient to correct for all dynamic motions, particularly where the vehicle is travelling at high speed and the road surface condition is poor.

C. ROAD ASSET MANAGEMENT DECISION MAKING

Road asset management can be considered to operate at four levels of decision making, namely planning, programming, preparation and operations [2]. The data requirements to support each level of decision making are different and can be defined according to the World Bank's information quality level (IQL) approach [35]. Table 3 summarises each level of management function together with their respective data requirements [2].

To assess the suitability of the approach, the outputs of the proposed system were compared with the values determined using the DVI data for the planning, programming and

TABLE 3. Road management functions.

Management function	Description	Data requirements	Information quality level
Planning	Analysis of the road network as a whole. Estimates are made of strategic, long-term expenditure requirements	Summary data of average of road network condition. Average values for 500 m up to 10 km lengths.	IQL-IV / IQL-III
Programming	Medium term asset management and involves the development of multi-year expenditure requirements.	Assessment of road condition over 0.3 - 1.0 km (by a minimum 5 measurements per section).	IQL-III / IQL-II
Preparation	Identification of actual road building and maintenance schemes.	Assessment of 20 - 200 m lengths of road (with a minimum of 5 measurements per section)	IQL-II / IQL-I
Operation	Detailed analysis of the condition of road sections in the immediate and short term.	Comprehensive detailed data at 3-20 m intervals [2]	IQL-I

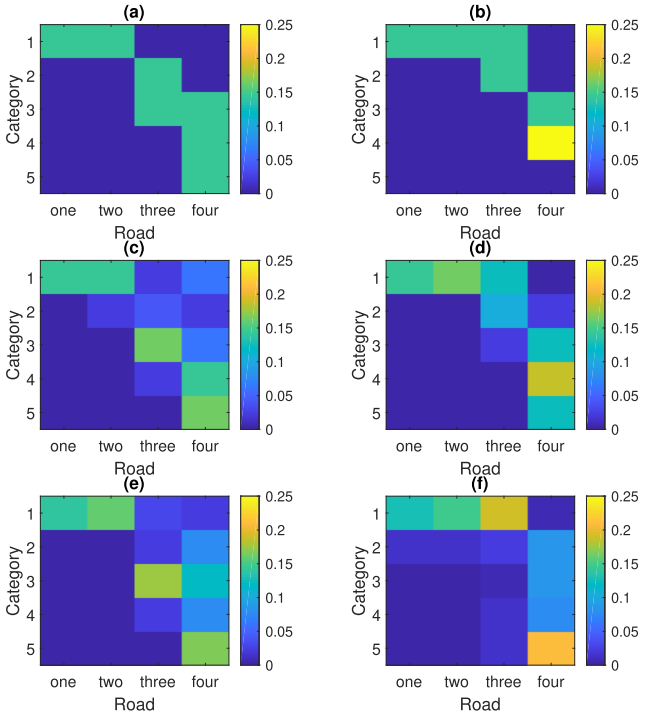

FIGURE 11. Comparison of results for the management function of Planning (a) DVI and (b) system, Programming (c) DVI and (d) system, Preparation (e) DVI and (f) system.

preparation levels of road management. As the DVI data is a measurement of the area of road surface per 20m length of road, it was not felt appropriate to compare the two datasets for the operation management function where data to a resolution of between 3-20m is required (see Table 3). For simplicity, the length of planning, programming and preparation are chosen as 500m, 60m and 20m respectively (cf. Table 3). In order to enable the comparison between the DVI data and system outputs, the condition of the four roads (cf. Table 1) were categorized into levels of fretting (i.e., Very Low, Low, Medium, High and Very High) according to the suggestion in [36] and segmented evenly based on the maximum values of each data. Fig 11 shows the number of 500m, 60m and 20m road segments categorised within each of the five levels of road condition as determined by the proposed approach and the DVI methodology. By inspection the proposed system

TABLE 4. T-test results for the three road management functions.

Road management function	Planning	Programming	Preparation
Measurement length	500 m	60 m	20 m
Number of measurement	7	49	144
Difference mean	0.28	0.22	0.14
Standard deviation	0.60	1.12	1.35
Standard error	0.23	0.16	0.11
t-value	1.247	1.399	1.483
$t_{0.05}$	$\pm$1.944	$\pm$1.645	$\pm$1.645

and the DVI approach show similar results for all three levels of road management. The similarity between the two approaches is greatest when the data is considered over 500m lengths of road (i.e., for the planning road management function). Conversely, there is some mismatch between the two methods at the preparation level of the road management function.

A paired difference test [37] was used to compare statistically the results of the proposed approach and the DVI methodology for each of the three levels of management. Using the t-test, the hypothesis that there is no difference between the fretting levels determined using the DVI method and the proposed approach was tested. Table 4 summarises the results of the analysis. The results in Table 4 show that statistically at the 95% confidence level, there is no difference in the fretting measured by the proposed approach and the visual DVI method when fretting levels are determined over road sections of 500m, 60m and 20m lengths of road. Thus, with reference to Table 3, the proposed approach can be considered appropriate for planning, programming and preparations (where categorisation of values is acceptable) levels of road management. In addition, the t-value increases as the measurement length decreases. This indicates that the performance of the proposed system improves as the length over which the average condition of a road section increases, confirming the results shown in Fig 11. It also indicates that the proposed point laser system can be used to categorise the amount of fretting on a road surface to a resolution of 20m, to an IQL level of 2-3.

VI. CONCLUSIONS

This paper presents a robust and low-complexity point laser system for rapid and network-level local road surveys. The proposed methodology includes a filtering process to remove the noise associated with the laser sensor and vehicle dynamic motions. A histogram analysis procedure is used to analyse the filtered data to determine the amount of fretting on the road surface. In order to take into account the road texture, the procedure compares the frequency distributions of the vertical distance of the road surface from the laser sensor, occurring in short (local) lengths of road and a longer (global) road section. The methodology is compared against a visual method of assessing fretting on four different roads with varying amounts of fretting.

A statistical analysis demonstrated that the developed system is capable of classifying the amount of fretting occurring in short road sections as accurately as a detailed visual inspection. Accordingly, the proposed system can provide data to IQL II-III which is sufficient for planning, programming and preparation levels tasks of road asset management decision making. However, further research is desired to improve the accuracy of the system so that it can enable condition surveys to be carried out to IQL I-II and thus enable the system to be used for operations management. Such improvements to the system could be made by using the inertial information from the IMU to allow for the vehicle's dynamic motion and thus reduce the need for the filtering approach suggested. Furthermore, an adaptive feature vector that can be modified according to the change in road texture could be developed to allow for improved accuracy where abrupt changes in road texture occur.

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