Improved non-contact 3D field and processing techniques to achieve macrotexture characterisation of pavements

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Abstract

Macrotexture is required on pavements to provide skid resistance for vehicle safety in wet conditions. Increasingly, correlations between macrotexture measurements captured using non-contact techniques and tyre-pavement contact friction are being investigated in order to enable more robust and widescale measurement and monitoring of skid resistance. There is a notable scarcity of research into the respective accuracy of the non-contact measurement techniques at these scales. This paper compares three techniques: a laser profile scanner, Structure from Motion photogrammetry and Terrestrial Laser Scanning (TLS). We use spectral analysis, areal surface texture parameters and 2D cross-correlation analysis to evaluate the suitability of each approach for characterising and monitoring pavement macrotexture. The results show that SfM can produce successful measures of the areal root mean square height ($\text{Sq}$), which represents pavement texture depth and is positively correlated with skid resistance. Significant noise in the TLS data prevented agreement with the laser profiler but we show that new filtering procedures result in significantly improved values for the peak density ($\text{Spd}$) and the arithmetic peak mean curvature ($\text{Spc}$), which together define the shape and distribution of pavement aggregates forming macrotexture. However, filtering the TLS data results in a trade-off with vertical accuracy, thus altering the reliability of $\text{Sq}$. Finally, we show the functional areal parameters $\text{Spd}$ and $\text{Spc}$ are sensitive to sample size. This means that pavement specimen size of 150 mm × 150 mm or smaller, when used in laboratory or field observations, are inadequate to capture the true value of areal surface texture parameters. The deployment of wider scale approaches such as SfM and spectrally filtered TLS are required in order to successfully capture the functional areal parameters ($\text{Spc}$ and $\text{Spd}$) for road surfaces.

Keywords:
- Pavement texture
- Macrotexture
- Skid resistance
- Structure from Motion (SfM)
- Terrestrial Laser Scanning (TLS)

1. Introduction

Adequate texture on the surface of a pavement is required to provide skid resistance or friction at the tyre/road interface for vehicle safety in wet conditions [1–4]. Skid resistance is also influenced by temperature, presence of contaminants, speed and tyre tread thickness [5]. Friction forces generated from the contact of the tyre with texture are a consequence of the viscoelastic deformation of the tyre, and increase in dry conditions with adhesion
Pavement texture is defined as the deviation of the pavement surface from a true planar surface [7] and has been characterised at different scales according to the wavelengths of the deviations [8]. Microtexture suspected to induce adhesion, represents the texture components with wavelengths from less than 0.5 mm and peak amplitude from 0.001 to 0.5 mm. Microtexture correlates to the asperities upon the surface of coarse road aggregates [9], and also to the fine particles present in the mixture constituting the wearing course of the pavement. In wet conditions, adhesion is reduced by the phenomenon of viscoplanning [6], where a degree of tyre contact is lost with the pavement due to the presence of a thin water film (in the order of a tenth of a millimetre or less).

Macrotexture, suspected to induce hysteresis response in the viscoelastic tyre, represents the texture components with wavelengths from 0.5 mm to 50 mm and amplitude of 0.1 mm to 20 mm mm (formed by the shape, size and graduation of road aggregates [10]. Thus, macrotexture, has been shown to influence the way skid resistance reduces with increasing speed in wet conditions [11]. Generally, with equal microtexture, pavement surfaces with higher macrotexture offer more friction resistance as speed increases than pavements with lower macrotexture under the same contact conditions [12,13].

Thus, the preservation of adequate skid resistance requires the monitoring of macrotexture [1] to ensure sufficient texture remains on the pavement to prevent skidding. Standard monitoring techniques involve either a sand patch test [14] or a direct measurement of the frictional resistance through a rubber pad [15] or test wheel making contact with a wetted pavement [16,17]. Kogbara et al. [18] provide a full summary of devices and their operating principles. These contact devices are known to be susceptible to seasonal variation [19]. This phenomenon has been attributed to a number of factors: the sensitivity of rubber resilience to temperature change [20]; changes induced by temperature in the viscosity of the test water of a device [21]; and differential polishing of the aggregate microtexture throughout the year [22].

Survey results obtained from these devices require statistical interpretation [1,23] with individual devices requiring harmonisation with the rest of a fleet [24]. Friction measurements from rubber contact base devices are also known to be susceptible to changes in travel speed [25]. Direct comparison between different devices adopted in particular countries is also difficult, as measurements are influenced by machine operating conditions such as the load, speed, slip ratio and the composition of the rubber.

The problems associated with contact measurement techniques, make a reliable non-contact technique desirable. Accurate non-contact macrotexture measurement is one step towards the estimation of pavement friction values via analytical modelling [5,26–28]. Researchers have successfully deployed contactless techniques under laboratory conditions to measure texture; typically to a size of 100 × 100 mm [29,30]. At present, there are also a number of in-situ proprietary spot contactless techniques available for use in the field, including the Circular Texture Meter [31], the Model 9300 laser texture scanner [32] and close-range stereo photogrammetry [33–35], which requires a minimum of three images taken from different perspectives to reconstruct a 3D pavement surface. These techniques offer an alternative to the simple sand patch test [14,36,37], where a measured volume of fine material is spread in a circular motion into a road’s surface depressions to find the mean texture depth, for in-situ localised pavement texture assessment. Recent research, focused on the development of a prototype test rig [38] adopting a laser range finder, that uses triangulation, to measure texture in the field or to detect defect on pavements [39], but is still restricted to a localised area comparable to that of a sand patch test. The minimum texture profile height measured by the rig was limited to 0.032 mm, with a spatial sampling frequency of about 4 mm⁻¹, thus meeting only part of the range needed for macrotexture. 3D handheld scanners [40,41], using triangulation principles, have also been deployed to capture macrotexture in-situ [42]. These scanners are designed for metrology applications, and having a limited field of view, lack scalability. Advances in ‘off-the-shelf’ laser and photogrammetry technology and point cloud post-processing applications means there is now the potential to capture macrotexture over larger areas, potentially more representative areas using contactless techniques. Terrestrial Laser Scanning (TLS) offers rapid, full 3D high resolution reconstruction of a highway surface as a point cloud [43] and Structure from Motion (SfM) photogrammetry [44,45] offers a low-cost method utilising digital images to generate a 3D dense point cloud data of surfaces.

This paper introduces a method to characterise macrotexture using TLS and SfM over a typical full lane width. Recent research [34] suggests that frictional resistance is sensitive to certain areal parameters [46,47] (Table 1). Particularly, to the density of peaks within the macrotexture of a highway surface, Spd, and to the pointiness or arithmetic mean of the principal curvature of the same peaks Spc; which together characterise the shape and size of the road aggregates. Furthermore, the areal parameters root mean square of surface departures, Sm, as the standard deviation of peak height from an average plane, is spatially equivalent to mean profile depth [48]. Mean profile depth represents the averaged values over an overall 2D profile length, of the difference within a lateral distance (typically in the order of a tyre/pavement contact) between the profile and a horizontal line through the top of the highest peak. This paper explores the accuracy of the scalable TLS

| Parameter Symbol | Parameter Name  | Description                                      | Calculation Equation                                      |
|------------------|-----------------|--------------------------------------------------|-----------------------------------------------------------|
| Sq               | Root mean square height | Root mean square value of the surface departures within the sampling area. | $S_q = \frac{1}{\sqrt{A}} \sqrt{\frac{1}{n} \sum_{x,y} z^2(x,y) dx dy}$ |
| Ssk              | Skewness        | Defines the shape of topography height distribution as a measure of symmetry about the mean line. | $S_{sk} = \frac{1}{\sqrt{A}} \frac{1}{3} \frac{1}{3} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} z^2(x,y) dx dy$ |
| Sp               | Maximum peak height | Largest peak height within a definition area A. | $S_p$ |
| Svm              | Maximum pit height | Smallest pit height value within a definition area A. | $S_{pm}$ |
| Spd              | Peak density    | The number of peaks per unit area. | $S_{pd} = \frac{n}{A}$ |
| Spc              | Arithmetic mean peak curvature | Measure of the principal curvature of the peaks, characterising the shape and size of the road aggregates. | $S_{pc} = \frac{1}{2} \sqrt{\frac{1}{2 \sum_{k=1}^{\infty} \left( \frac{1}{k} \right)^2 \int_{0}^{1} \frac{z^2(x,y) dx dy}{\sqrt{A}}}$ 
and SFM approaches to determining these measurements in comparison to measurements achieved using a 3D Smart Laser Profile Sensor [49]. The 3D Smart Laser Profile Sensor was selected as an accurate well-constrained controlled dataset of 2D profile macrotexture measurements from which to formulate a 3D surface, as such laser profile sensors are well-understood have been deployed widely previously to capture 2D profile measurements of macrotexture [50–52]. This paper will first introduce the methods applied to capture point cloud data in the field using the three techniques, before rigorously considering the accuracy of results obtained through the application of spectral analysis, areal parameters and 2D cross-correlation.

2. Methods

2.1. Remote sensing technology

2.1.1. Terrestrial Laser scanning

The TLS data were collected using the Faro Focus 3D X Series phase-based laser scanner on a tripod mounted inverted as shown in Fig. 1a. The static scanner was set-up at a height of 1 m above the pavement surface on a levelled tripod, and the desired scanning parameters were entered on the instrument’s home screen. Fig. 2 details the workflow for programming the scanner’s settings prior to completing a scan. To retain a practical completion time for the survey, a resolution of 1/5 and quality of 6× was adopted, providing a scan time of 22.38 min. The scanner stores data on a SD memory card, and this was post processed using Faro Scene 7.1 software to extract, register and align the point cloud.

2.1.2. Structure from Motion photogrammetry

Static digital images (5472 × 3648 pixels) were captured at the test location using a digital single-lens reflex camera with 50 mm fixed focal length, mounted on a camera tripod and dolly (refer to Fig. 1b). Following the method of [34] a minimum of 60% forward overlap and 30% sideways overlap between photographs was maintained. Previous research [45] has demonstrated that capturing flat surfaces using SFM with predominantly parallel images, and adopting self-calibration of camera locations can cause deformation of the point cloud typified by ‘doming’ effects. To prevent these affects, overlapping photographs, were captured at three heights (500 mm, 600 mm and 750 mm) above the pavement surface, across the width of the highway (Fig. 3a).

Agisoft Photoscan version 1.3.4.5067 software 6 was used to post process the images enabling reconstruction of the overlapping photographs into a 3D point cloud. The software determines the position and orientation of cameras automatically using a scale invariant feature transform (SIFT) [44]. The SIFT matches up identified features across the image set, to establish their 3D co-ordinates and generate a sparse cloud. The sparse cloud is then densified into a dense point cloud by the software using Multi View Stereo techniques [53]. Fig. 3 illustrates the key stages of the construction of a point cloud from the camera images. Using this approach, an area equivalent to the width of a standard road lane (3.65 m) was successfully reconstructed without deformation.

2.1.3. 3D smart laser profiling

The 3D Smart Laser Profile Sensor, an LMI Technologies Gocator 2350, was mounted upon a trolley at a height of 500 mm (Fig. 1c) and powered by a 60-volt battery. One trolley wheel made contact with a digital quadrature encoder fitted to a 200 mm circumference measuring wheel. The digital encoder was wired to provide a pulse signal to the 3D Smart Sensor, being programmed to produce 40,000 pulses per rotation of the measuring wheel. Each pulse equates to a travel distance of 0.005 mm and this information is used to enable 3D surface profiles to be captured at variable speed. The 3D Smart Laser Profile Sensor’s settings where programme using Gocator Emulator version 4.6.7.17 software, installed on a conventional laptop. Fig. 2b details the workflow for programming the 3D Smart Laser Profile Sensor’s settings prior to completing a scan. The data were collected at walking speed every 201 pulses or 1.005 mm over a 3 m section, with the 3D Smart Laser Profile Sensor operating at a typical field of view width of 300 mm. The 3D Smart Laser Profile Sensor, is equipped with the capacity to view the laser points forming the profile line on the highway surface in ‘real-time’. This facilitates adjustment of the laser exposure level and active measurement area to accommodate ambient light levels, stray light and variability of highway surface reflectivity.

Fig. 1. Equipment set-up for: (a) Terrestrial Laser Scanner. The Faro Focus 3D X Series scanner is fitted onto a tripod stand (i) using an invert head fitting (ii). (b) Structure from Motion. A digital single-lens reflex camera with 50 mm fixed focal lens (iii), is mounted on a standard Leica camera tripod (iv) and dolly (v). (c) 3D Smart Laser Profile Sensor. LMI Technologies Gocator 2350 laser profile sensor (vi) is fixed at a height of 500 mm to the trolley frame and operated using Gocator Emulator version 4.6.7.17 software installed on a standard laptop (vii). A quadrature digital encoder fitted to a 200 mm measuring wheel (viii) enables images to be captured at variable speed up to a maximum of 10 km/h. The system is powered by a 60-volt battery (ix).
The surface profiles extracted from the 3D Smart Laser Profile Sensor were post processed using Gocator_Emulator version 4.6.7.17 and kCSvConverter software to an ASCII xyz file format suitable for point cloud post processing [54].

2.2. Test location

To test the three techniques a field site was selected that contained three standard types of pavement surface within close proximity (Fig. 4), allowing for the same ambient conditions to be assumed over the surfaces. The site included a close graded dense bitumen macadam (DBM), and a gap graded hot rolled asphalt (HRA), as well as surface dressing (SD). Test were undertaken on the dry pavement surfaces with permanent ground control points being installed to demarcate each surface using 16 mm survey nails.

2.3. Deriving macrotexture parameters from non-contact survey techniques

The 3D point cloud data for the DBM, HRA and SD surfaces were captured consecutively on the same day using the three different techniques. The point clouds obtained from each technique were then aligned utilising the installed reference ground control points in Cloud Compare v 2.10 software [55], to facilitate direct comparison between the surfaces. Subsequently, 150 mm x 150 mm sample areas (representing a typical laboratory specimen size) were clipped for each surface from the aligned point clouds for analysis. These clipped point clouds were then loaded into MountainsMap Premium version 7.4 and the software used to remove any transverse or longitudinal slope by method of least squares, and to calculate the standard areal parameters as listed in Table 1, to characterise the macrotexture. Areal parameters were adopted, in contrast to 2D profile parameters [56], as these are recognised as providing a more complete description of a surface [46], capturing height with respect to both the ‘x’ and ‘y’ direction to characterise functional aspects such as texture, shape and direction. In sampling the point cloud data to make successful areal measurements it is important that Nyquist values be smaller than the smallest desired surface macrotexture requiring characterisation. Nyquist sampling theorem states that the shortest wavelength that can be defined from a digital dataset is two digital sample intervals long. Therefore, the wavelength or sample length available to characterise pavement texture areal parameters, is defined by the relationship between point cloud density and sample size.

2.4. Deriving 2D wavenumber amplitude spectra from non-contact techniques and filtering

Image datasets can be analysed by MATLAB software to transform them to the wavenumber domain, allowing images to be characterised by spatial frequency. Accordingly, 2D Kx-Ky wavenumber spectral analyses of the samples [56] were calculated in MATLAB to determine the areal wavenumber characteristics of the surfaces captured using the different techniques. To prevent spectral leakage caused by discontinuities at the edges of each measured sample area, the amplitude of the signal at the outer edges was attenuated using a cosine taper Tukey window that extended for 10% from the extreme edges of the sample line [57]. The resulting 2D wavenumber spectra enabled the wavenumber content of the data to be determined, which facilitated the selection of an appropriate 2D wavenumber filter to attenuate high wavenumber noise from the macrotexture signal.
Examining the spectra for each non-contact technique the 3D Smart Laser Profile Sensor was the lowest resolution technique, containing wavenumbers not greater than 0.1 mm\(^{-1}\). Consequently, to achieve conformity of the wavelengths for areal parameter analysis across techniques a wavenumber filter of 0.1 mm\(^{-1}\) was applied to the SFM and TLS data. A low pass zero phase Butterworth wavenumber filter was then designed to remove high wavenumber noise components from the data, up to the Nyquist wavenumber. The filter was applied in a two-pass process, firstly for every trace in the x-direction and then the y-direction, thus creating a 2D filtered data set. Normalised 2D autocorrelations and cross-correlation plots of the filtered surface data were then prepared as a means of measuring image spatial similarity (as the macro-texture scale pushes the limit of conventional differencing techniques adopted for identifying similarity and change in point cloud analysis).

3. Results and discussion

Nyquist values are given in Table 2. The 3D Smart Laser Profile Sensor minimum Nyquist wavelengths mean that the technique is unable to measure a small part of the lower range of macrotexture wavelengths between 0.5 and 1 mm. The SFM and TLS Nyquist wavelengths mean the techniques can measure the full range of macrotexture wavelengths and have the potential to also measure some part of microtexture below 0.5 mm, this capability should be explored as part of a further research study. The Nyquist wavelengths vary between samples, possibly because the techniques are sensitive to pavement surface albedo, environmental conditions, and edge effects. Given technique sensitivity, oversampling to ensure a sufficiently fine Nyquist wavelength is beneficial and in this regard adopting a higher resolution technique such as TLS is advantageous. The Nyquist wavelength for a TLS, will increase with distance from the laser source, because of the elongation of the beam, as the angle of incidence with a surface increases. Therefore, the optimal location to acquire TLS data with an ‘off-the-shelf scanner’, is within a narrow cone of incidence directly in line with the laser source, with data captured using an inverted head tripod set-up.

Surface height plots for each surface scanning technique are illustrated in Fig. 5. For the DBM greater similarity is evident between Fig. 5(a) and (b) as the 3D Smart Laser Profile Sensor and SfM techniques have similar resolution. The higher resolution of the TLS is evident in the finer granularity of plot Fig. 5(c). All the techniques are able to capture the voids between aggregates (e.g. i) and aggregate features (e.g. ii) on the DBM surface at the same locations. Equally, for the HRA surface there is greater similarity...
between Fig. 5(e) and (f), the data captured with the 3D Smart Laser Profile Sensor and SfM techniques. The higher resolution of the TLS is evident again in the finer granularity of the edges of the red chipping aggregate (Fig. 5g). Finally, although the SD aggregates in blue Fig. 5(J)–(l) (e.g. vi) and areas of elevated macrotexture in orange located to the right and left edge of each plot. Again there is greater similarity between Fig. 5(j) and (k), the data capture with the 3D Smart Laser Profile Sensor and SfM technique. The higher resolution of the TLS is evident in the finer granularity of plot (i). The degree of similarity between the techniques has been characterised using areal parameters and 2D correlation analysis discussed in Section 3.1 and 3.2 respectively.

3.1. Unfiltered areal parameters

The areal parameters derived for each technique are given in Table 2. $S_q$ is spatially equivalent to the mean profile depth that is used at present to evaluate macrotexture. Table 2 shows that $S_q$ for the 3D Smart Laser Profile Sensor and SfM are within 0.002 mm agreement for the DBM, 0.013 mm for the SD and 0.09 mm for the HRA. This presents the 3D Smart Laser Profile Sensor and SfM, as an alternative method to capture texture depth. The TLS obtained results for $S_q$ are very different, with differences in comparison with the 3D Smart Laser Profile Sensor value ranging from 0.139 mm to 0.394 mm; the largest value being obtained for the SD surface. The value for $Sp$ and $Sv$, the maximum peak and pit heights, demonstrate greater agreement between the SfM and 3D Smart Laser Profile Sensor results, than the TLS technique. The variance in TLS derived parameters is because of the higher resolution of the TLS is evident again in the finer granularity of the edges of the data capture with the 3D Smart Laser Profile Sensor and SfM technique.

Table 2

| Parameter          | Point Density | Nyquist Wavelength | $S_q$ (mm) | $S_{sk}$ | $Sp$ (mm) | $Sv$ (mm) | $Sp_d$ (mm$^{-1}$) | $Sp_c$ (mm$^{-1}$) |
|--------------------|---------------|--------------------|------------|----------|-----------|-----------|-------------------|-------------------|
| Unfiltered         |               |                    |            |          |           |           |                   |                   |
| Dense bitumen macadam | Smart sensor |                    | 0.97       | x = 1.02 | y = 1.02  | 0.951     | –0.321            | 2.21              |
|                    | SfM           |                    | 35.80      | x = 0.167| y = 0.167 | 0.949     | –0.711            | 1.80              |
|                    | TLS           |                    | 83.59      | x = 0.091| y = 0.131 | 1.090     | –0.124            | 4.99              |
| Hot rolled asphalt | Smart sensor  |                    | 4.19       | x = 0.489| y = 0.489 | 1.280     | –1.040            | 2.93              |
|                    | SfM           |                    | 26.47      | x = 0.194| y = 0.206 | 1.370     | –0.901            | 3.13              |
|                    | TLS           |                    | 163.84     | x = 0.073| y = 0.083 | 1.560     | –0.215            | 6.18              |
| Surface dressing   | Smart sensor  |                    | 3.39       | x = 0.547| y = 0.539 | 0.544     | –0.680            | 1.58              |
|                    | SfM           |                    | 31.19      | x = 0.145| y = 0.222 | 0.557     | –0.743            | 1.76              |
|                    | TLS           |                    | 63.27      | x = 0.142| y = 0.111 | 0.938     | –0.267            | 3.89              |
| Filtered           |               |                    | 0.66       | x = 1.23 | y = 1.23  | 3.940     | –0.565            | 9.78              |
| Dense bitumen macadam | Smart sensor |                    | 24.37      | x = 0.202| y = 0.204 | 3.660     | –0.947            | 9.30              |
|                    | SfM           |                    | 55.67      | x = 0.120| y = 0.150 | 0.738     | –0.654            | 2.24              |
| Hot rolled asphalt | Smart sensor  |                    | 3.74       | x = 0.519| y = 0.515 | 12.600    | –0.972            | 30.30             |
|                    | SfM           |                    | 23.95      | x = 0.194| y = 0.215 | 13.100    | –0.937            | 30.10             |
|                    | TLS           |                    | 148.19     | x = 0.078| y = 0.087 | 3.200     | –0.233            | 7.45              |
| Surface dressing   | Smart sensor  |                    | 2.31       | x = 0.664| y = 0.652 | 2.000     | –0.801            | 4.91              |
|                    | SfM           |                    | 20.61      | x = 0.194| y = 0.250 | 2.390     | –0.947            | 5.98              |
|                    | TLS           |                    | 42.63      | x = 0.165| y = 0.142 | 0.607     | –0.741            | 1.50              |

3.2. 2D correlation analysis

Areal parameters only characterise discrete functions of surface roughness. Therefore, 2D cross-correlation analysis to measure $x$-$y$ and $z$ plane similarity between images was completed. Perfect cor-
The normalised 2D cross-correlation plots are shown in Fig. 6. For the DBM surface a central peak is evident of 0.4492 and 0.3515 for similarity between the 3D Smart Laser Profile Sensor and SfM, and 3D Smart Laser Profile Sensor and TLS respectively (Fig. 6(a) and (d)); defining positive correlation and symmetry (or lack of shift) between the wavelength frequencies. To the left of the central peak there is a dominating positive feature on both plots, depicted as the yellow to red zone (e.g., Fig. 6(a)–(i)), representing an area of higher macrotexture departure from the surface. For the SD surface, no central peak is evident with elongated bands of positive and negative agreement being visible (Fig. 6cii and ciii) for similarity between both the 3D Smart Laser Profile Sensor and SfM, and 3D Smart Laser Profile Sensor and TLS. The bands arise as the macrotexture of the SD surface is dominated by a repeating texture feature.

Overall, the best correlation is achieved between the 3D Smart Laser Profile Sensor and SfM measurement technique for the HRA surface Fig. 6(b). The plot has a clear strong centralised peak of 0.729, demonstrating an alignment or lack of lateral shift between the wavelength frequencies of the two techniques. The rest of the plot is generally blue indicating a general lack of secondary dominating features on the surface. This can be attributed to the parity of resolution between two techniques and the larger wavelength features of the HRA surface. The 2D cross-correlations affirm the areal parameter results with greater agreement between the unfiltered 3D Smart Laser Profile Sensor and Structure from Motion technique. The 2D cross-correlation plots comparing similarity between the 3D Smart Laser Profile Sensor and TLS demonstrate less agreement. The normalised cross-correlation peaks are either not present or where present are lower being 0.3515 for the DBM (Fig. 6(d)). This confirms the influence of the higher resolu-
tion shorter wavelengths within the unfiltered data, which cause the reduction in the normalised peak, and reduced agreement. After the application of a 0.1 wavenumber filter the heights of the normalised 2D cross-correlation peaks increase by 16.6–25% demonstrating stronger agreement between the 3D Smart Laser Profile Sensor and the other two techniques.

### 3.3. Filtered areal parameters

Surface height plots for each filtered surface scanning technique are illustrated in Fig. 7. For all three surfaces after the application of a 0.1 mm⁻¹ wavenumber filter there is greater visual similarity between all three techniques. The filter has reduced the resolution of the TLS data, removing the finer granularity, to reveal the macrotexture more clearly. Furthermore, post-filtering increased agreement was achieved for areal parameters Spd and Spc, previously shown to have a positive correlation with skid resistance. The filtered areal parameters are shown in Table 2. The filtered Spc (arithmetic mean peak curvature) values, related to the shape of the road aggregates, measured using the 3D Smart Laser Sensor and SfM are within 0.013 mm⁻¹ for the DBM and 0.067 mm⁻¹ for the SD. The filtered values of Spc for the HRA do not demonstrate agreement. The filtered Spd (peak density) values, related to the distribution of road aggregates upon a pavement surface, measured using the 3D Smart Laser Sensor and SfM are within 0.00087 mm⁻² for the DBM, 0.01417 mm⁻² for the HRA, and 0.00044 mm⁻² respectively for the SD. The filtered Spd (peak density) values measured using the 3D Smart Laser Sensor and TLS are within 0.00059 mm⁻² for the DBM, 0.01747 mm⁻² for the HRA, and 0.00054 mm⁻² for the SD. The filtered Spd values measured using the SFM and TLS are within 0.00028 mm⁻² for the DBM, 0.0033 mm⁻² for the HRA, and 0.0001 mm⁻² for the SD. Although an increased agreement has been achieved for Spd and Spc, importantly for practical pavement characterisation of surface height departures, for the 3D Smart Laser Profile Sensor and SfM techniques this is at the expense of the accuracy of Sq, which experiences magnification at a range of four to ten times. Therefore, filtering improves spatial agreement, but at the cost of vertical measurement, a factor that should be considered by researchers seeking correlations between non-contact texture measurements.
and skid resistance. Moreover, the filtered values of $S_q$ obtained from the TLS whilst closer to the original unfiltered 3D Smart Laser Profile Sensor, demonstrate at best ten percent accuracy; being in 0.213 mm agreement for the DBM, 1.928 mm agreement for the HRA and 0.063 mm agreement for the SD. The TLS technique does offer the best balance between the vertical and spatial areal functions post-filtering, fundamentally because it enables oversampling of the surfaces, with correspondingly the shortest Nyquist wavelength. However, the improved resolution of the technique still does not lead to sufficiently accurate measurement of $S_q$, the vertical departure heights from a pavement surface. Greater technique resolution does not necessarily equate to sufficiently improved accuracy for some measurements.

### 3.4. Spectral analysis

The spectra in Fig. 8 illustrate the areal wavenumber characteristics of the three surface materials in the ‘x’ and ‘y’ plane [55]. As wavenumber is the reciprocal of wavelength, the plots serve to demonstrate differences in macrotexture characteristic between the surfaces. The spectra are sensitive both to the scale of the macrotexture and the technique of measurement. The TLS has the largest spectral cloud of the three techniques for all surfaces, illustrating that it is consistently the highest resolution technique. Considering the SfM spectral plots, it is clear that the HRA surface has the largest wavelength features represented by the brightest spectral cloud centre; whilst the DBM contains the smallest wave-
As a high pass filter was not applied to the cloud data, the larger wavelengths in the centre of the spectral plots represent the unevenness of the surfaces. The spectra reveal for the SFM technique that for the HRA the wavelengths features are typically 4 mm or larger; the SD 3.5 mm or larger and DBM 2.6 mm or larger. Finally, greater similarity is generally evident between the unfiltered spectra for the SFM and 3D Smart Laser Profile Sensor, as the techniques have similar resolution and accuracy.

3.5. Spatial variability

The spatial variability of $S_q$, $S_{sk}$, $S_p$, $S_v$, $S_{pd}$ and $S_{pc}$ for seventy-two 150 mm × 150 mm samples and eighteen 300 mm × 300 mm samples captured using SFM were considered for a 1.8 m × 0.9 m area of HRA in Figs. 9 and 10.

The computed parameters ($S_q$, $S_{sk}$, $S_p$, $S_v$, $S_{pd}$ and $S_{pc}$) for each individual sample, were divided into a percentage of the overall maximum for each considered areal parameter, with the discrete colour contrasts representing 20%. Thereby each colour represents a 20th percentile in the overall maximum parameter value, and thus illustrates the variability of the parameters across the 1.8 m × 0.9 m HRA surface. The 150 mm × 150 mm sample size for $S_p$, maximum peak height, reflects the distribution of red aggregate chippings across the HRA surface. Lower peaks are encountered near the top edge of the sample, where the surface is predominantly bituminous binder. Some discrete squares of increased peak height are shown in dark green, representing the
higher texture height of isolated red chippings. Principally, the peak height values \( Sp \) are within the percentile range of 1.85 mm to 3.65 mm. The 150 mm \( \times \) 150 mm sample size for \( Sv \), maximum pit height, demonstrated limited variability between separate sample areas, with 87.5% of the HRA surface being within 4.4–7.4 mm. This consistency most likely reflects the method of laying HRA, with the precoated red aggregate chippings being scattered across the surface of the previously laid asphalt binder and rolled into the surface at a constant pressure, resulting in more consistent pit heights. For vertical macrotexture characterisation parameters, such as \( Sv \), \( Sp \) and \( Sq \) spatially equivalent to the mean profile depth used at present to evaluate macrotexture, there is some similarity between the location of darker colour contrast for both the 150 mm \( \times \) 150 mm and 300 mm \( \times \) 300 mm sample sizes.

There is a lack of parity between the surface characterised using the 150 mm \( \times \) 150 mm sample and the 300 mm \( \times \) 300 mm sample for \( Spd \); with an increase in sample size appearing to ‘smooth’ the density of peaks removing altogether the highest percentile range.
3.42 × 10^{-3} \text{ mm}^{-2} \text{ to } 4.06 \times 10^{-3} \text{ mm}^{-2} \text{ from the 300 mm × 300 mm plot. The 150 mm × 150 mm samples reflect the distribution of red chippings across the surface, with the lower peak densities recorded near the top and edge of the HRA surface where there is predominantly bituminous binder present. The } Spd \text{ parameter also demonstrates the greatest variability between different 150 mm × 150 mm samples. } Spd \text{ has previously been shown as being important to skid resistance, with positive correlation achieved with friction measurements. However, the variability of } Spd \text{ values, means picking a representative 150 mm × 150 mm sample to characterise the whole surface to correlate with friction is difficult. } Spd \text{ represents the number of peaks in a unit area and is sensitive to sample size. Fig. 11 considered the influence of upscaling the sample size for areal parameters ( } Sq, Ssk, Sp, Sv, Spd \text{ and } Spc \text{) on the HRA surfacing capture using SFM with the point cloud extended to 1.05 m × 1.95 m. For } Spd \text{ the optimum sample size for the HRA surface was found to be 1050 mm × 1050 mm. For the vertical macrotexture parameters, the optimum sample size was found to be 750 mm × 750 mm for } Sv, 1050 mm × 1200 mm for } Sp, \text{ and 1050 mm × 1650 mm for } Sq.

For } Spc \text{ mean curvature of peaks, the optimum sample size was discovered to be 450 mm × 450 mm for the HRA surface. } Spc \text{ was

| Sample Reference | Size (mm)   | Sample Reference | Size (mm)   |
|------------------|-------------|------------------|-------------|
| A                | 150 x 150   | G                | 1050 x 1050 |
| B                | 300 x 300   | H                | 1050 x 1200 |
| C                | 450 x 450   | I                | 1050 x 1350 |
| D                | 600 x 600   | J                | 1050 x 1500 |
| E                | 750 x 750   | K                | 1050 x 1650 |
| F                | 900 x 900   |                  |             |

Fig. 11. The influence of upscaling sample size on areal parameters } Sq, Ssk, Sp, Sv, Spd \text{ and } Spc \text{ for an area of Hot Rolled Asphalt surfacing captured using Structure from Motion. The optimum sample size for each parameter is indicated on each graph with a dotted line, and occurs where values converge to a stable value.}
found to have the smallest sample size of all the parameters considered perhaps reflecting its general lack of heterogeneity. The 150 mm × 150 mm sample size demonstrating the least variability across the HRA surface of any of the areal parameters considered by the study; with 80% of the samples falling within the 20% range of 0.58 mm⁻¹–0.88 mm⁻¹.

Whilst Sqq, Spd, and Sv just capture the overall height and depth of peak and pit surface departures, Sik gives the location (or skewness) above and below the mean plane; consequently, providing an indication of the distribution of texture available to contribute to skid resistance. For Sik, both the 150 mm × 150 mm and 300 mm × 300 mm sized samples confirm that the HRA has positive texture. The split of the contrasting light and dark blue squares for Sik, is similar for each sample size, with the predominant number of darker squares below the white diagonal line bisecting the 1.8 m × 0.9 m area (refer to Fig. 10). However, the location of the mean plane was determined to be sensitive to sample size, with the value of Sik varying. A sample size of 1050 mm × 1200 mm of smaller was found in the upsampling analysis to have a negative texture confirming a positive texture, but above this size Sik was shown to have a positive value indicating a skew to negative texture. The change in Sik can be attributed to the influence of the variability of peak height with changing sample area, on the location of the mean plane. Overall reviewing individual areal parameters typically used to characterise friction (Sp, Sv, Spd and Spc) optimal sample size, suggests that a suitable sample size of 1050 mm × 1200 mm is appropriate to characterise HRA; this being established from the maximum size of the individual parameters

Further research should be conducted to explore the efficiency of sample sizes for areal parameters for different pavement textures. As contact friction devices are known to be susceptible to seasonal variation and machine operating conditions such as load, speed slip ratio and the composition of rubber, using reliable non-contact areal parameter data to be able to analytically model a relationship with friction is desirable. Moreover, higher resolution does not always equate to greater accuracy. It was found that whilst SFM photogrammetry successfully provides an alternative method to the 3D Smart Laser Profile Sensor to capture vertical pavement measurement Svv, Svv and Ssq for mean profile depth estimation and correlation with friction, the higher resolution TLS data contained significant inaccuracies. Furthermore, the values of Spd and Sqc, which together define the shape and distribution of pavement aggregates and have previously been proven to have positive correlation with friction [34], are sensitive to resolution, incurring order of magnitude differences. A 2D low pass wavenumber filter achieved improved agreement with the 3D smart profiler for Spd and Sqc parameters. Optimising such filters consistently across a range of non-contact techniques is needed to achieve a ‘universal’ correlation between these parameters and to model relationships with skid resistance. Further, as the application of such a filter has the potential to impact on vertical accuracy of measurement (Sqq, Spp, and Sv) for some high resolution techniques, findings of this study indicate the filter should be applied only to the Spd and Sqc spatial parameters.

4. Conclusions

In conclusion, the study has compared the measurement of macrotexture using three different techniques. The study makes a first contribution to the establishment of reliable standardised texture measurements using point cloud derived data to inform analytical prediction methods for tyre-pavement contact friction without the influences of seasonal variation, measuring devices and their operating conditions. Results from the analysis of the data lead to the following conclusions:

- Unfiltered close field SFM photogrammetry provides values of Sp, Sv and Sqq within an acceptable degree of tolerance to those obtained from the 3D Smart Laser Profile Sensor, so as SFM photogrammetry is an effective, readily scalable alternative method to capture mean profile depth for pavement evaluation.
- The parameters Sqc and Spd, for which previous studies have established an important correlation with pavement friction, are sensitive to technique resolution and a 2D low pass wavenumber filter needs to be applied to obtain a ‘universal’ measurement for pavement friction assessment.
- A 2D zero-phase wavelength filter of 0.1 mm⁻¹ improves Spd, for the TLS and SFM techniques.
- The Nyquist wavelengths of TLS and SFM techniques mean they have the potential to measure microtexture wavelengths below 0.5 mm.
- TLS data are significantly improved for macrostructure surveys after 2D low pass wavenumber filtering.
- Where 150 mm × 150 mm industry sample sizes are used to determine parameters from point clouds data derived from non-contact techniques, these are not sufficient to correctly characterise functional areal parameters to describe the spatial variability of macrotexture upon a pavement. This study suggests a suitable sample size of 1050 mm × 1200 mm is appropriate to characterise HRA.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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