

WAVELET DE-NOISING OF TERRESTRIAL LASER SCANNER DATA FOR THE CHARACTERIZATION OF ROCK SURFACE ROUGHNESS

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ABSTRACT:

The application of terrestrial laser scanning to the study of rock surface roughness faces a major challenge: the inherent range imprecision makes the extraction of roughness parameters difficult. In practice, when roughness is in millimeter scale it is often lost in the range measurement noise. The parameters extracted from the data, therefore, reflect noise rather than the actual roughness of the surface. In this paper we investigate the role of wavelet de-noising methods in the reliable characterization of roughness using laser range data. The application of several wavelet decomposition and thresholding methods are demonstrated, and the performances of these methods in estimating roughness parameters are compared. As the main measure of roughness fractal dimension is derived from 1D profiles in different directions using the roughness length method. It is shown that wavelet de-noising in general leads to an improved estimation of the fractal dimension for the roughness profiles. The choice of the decomposition method is shown to have a minor effect on the de-noising results; however, the application of hard or soft thresholding mode does have a considerable influence on the estimated roughness measures. The presented results suggest that hard thresholding yields more accurate de-noised profiles for which the estimated roughness measures are more reliable.

1. INTRODUCTION

The measurement of the surface roughness of rock masses has been traditionally based on manual measurement tools such as carpenter's comb and compass and disc clinometers. The manual measurements are limited to small samples at accessible parts of the rock. Terrestrial laser scanning is an attractive alternative measurement technique, which offers large coverage, high resolution, and the ability to reach inaccessible high rock faces. A fundamental limitation of this technique, particularly in the characterization of rock surface roughness in millimeter scale, is the measurement noise inherent in laser scanner data. In general, error in laser scanner data may originate from three main sources: the imprecision of the scanning mechanism and the ranging technique (Dorninger et al., 2008), environmental conditions (Borah and Voelz, 2007) and the physical and geometric properties of the scanned surface itself (Soudarissanane et al., 2009). Normally, the systematic components of the error are eliminated or modeled through a proper calibration procedure (Lichti, 2007). The remaining random error is in the order of a few millimeters for a typical medium-range (1-150 m) terrestrial laser scanner, and is commonly referred to as measurement noise.

The effect of laser scanner measurement noise on roughness characterization has been pointed out in a few previous studies. Fardin et al., (2004) reported that the fractal dimension obtained from raw laser data of a rock face is larger than the expected range (according to Kulatilake and Um (1999) 1.2-1.7 for 1D profiles, and 2.2-2.7 for 2D patches). They attributed the overestimated roughness to the irregular distribution of the points in the original point cloud, and performed an interpolation of the points into a uniform distribution to reduce the fractal dimension to within the expected range. Rahman et al., (2006) suggested that the overestimation of surface

roughness obtained from raw laser data is due to the fact that roughness measures reflect more noise in the data than the actual roughness of the surface. They used radial basis functions to interpolate the data into a smooth surface, which resulted in roughness measures within the expected range. Although data smoothing by interpolation has been the common approach to reduce the influence of noise on roughness characterization, it is generally not considered an adequate noise reduction method (Gonzalez and Woods, 1992). The basic assumption in data smoothing is that the measured surface is actually smooth and so by smoothing one can reduce the noise without degrading the data related to the actual surface. As this assumption is not valid when dealing with rough surfaces, the result of data smoothing is the loss of roughness information. Thus, a careful treatment of noise in laser range data is of great significance if a realistic characterization of rock surface roughness is of concern. In this paper we investigate the influence of range measurement noise on roughness characterization of rock surfaces using the roughness length method (Malinverno, 1990). We demonstrate the application of wavelet transform (Hardle et al., 1998; Strang and Nguyen, 1996) to removing noise from roughness profiles derived from laser scanner point clouds, and compare the performance of various wavelet decomposition and thresholding methods in the context of surface roughness characterization.

The paper proceeds with an overview of the laser scanning technique and the derivation of roughness profiles from laser range data in Section 2. In Section 3, the principles of wavelet-based de-noising are presented along with a description of various decomposition and thresholding methods. Section 4 reports the experimental analysis of the influence of noise on roughness characterization and the results of wavelet de-noising of roughness profiles. The paper concludes with some remarks in Section 5.

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2. ROCK SURFACE ROUGHNESS FROM LASER RANGE DATA

Laser scanning is an active measurement technique based on emitting laser beams to a surface of interest and recording the reflections. A scanning mechanism, usually a rotating mirror, deflects the emitted beam towards the surface in such a way that the entire surface is scanned at regular horizontal and vertical angular intervals. The range measurement principle in medium-range terrestrial laser scanners is most often based on the phase difference between the emitted and received waveforms. From the measured range and horizontal and vertical scan angles, 3D coordinates are computed for each point in a Cartesian coordinate system with its origin at the centre of the scanner. Today's laser scanners can measure more than a hundred thousand points per second at an angular resolution smaller than 0.01 degrees (see for instance Faro (2009)). By scanning at such high resolution from a few tens of meters distance to a rock face one can acquire a dense point cloud that represents the geometry of the scanned surface in great detail.

Before roughness information is derived from a point cloud it is convenient to rotate the point cloud such that surface roughness corresponds to variations in the direction of Z axis. Based on the assumption that the point cloud represents a more or less flat surface, the rotation can be computed simply by performing the principal components analysis (Jolliffe, 2002). The eigenvectors and eigenvalues of the covariance matrix of the points describe the axes of maximum and minimum variation in the point cloud, and provide a transformation of the points to these principal axes. By fitting a smooth (usually planar) surface to this rotated point cloud a representation of the roughness as the residual height of the points can be obtained.

A common method for roughness characterization, which is also adopted in this paper, is the fractal-based roughness length method (Malinverno, 1990). In this method, roughness is characterized by two measures: fractal dimension and amplitude. Both measures can be derived from a 1D profile or a 2D patch extracted from the point cloud. In either case, the roughness measures are estimated based on a power law relation between the standard deviation of the residual height of the points, s , and the length of a sampling window w :

$$s(w) = Aw^H \quad (1)$$

where parameters A and H are called amplitude and the Hurst exponent respectively. These parameters are estimated from the intercept and slope of a log-log plot of s versus w for several lengths of the sampling window. The main measure of roughness is the fractal dimension, which is derived from the

Hurst exponent as $D = 2-H$ for a 1D profile, and $D = 3-H$ for a 2D patch. A large fractal dimension indicates a very rough surface with abrupt changes of the residual height whereas a small fractal dimension implies a smooth surface without much roughness. More details on the estimation of fractal dimension for 1D profiles can be found in Kulatilake and Um (1999), and for 2D patches in Fardin et al., (2004). In the rest of the paper we focus on the characterization of roughness in 1D profiles.

3. WAVELET DE-NOISING OF ROUGHNESS PROFILES

Wavelet de-noising is based on the wavelet transform (Strang and Nguyen, 1996) for decomposing a signal into several components of different scale and resolution. The basic principle is that high-frequency components are more likely to contain noise than low-frequency components that contain the general trend of the signal. The purpose of wavelet decomposition in de-noising laser range data is to remove noise only from the high frequency components so as to preserve the low frequency content of the data as much as possible. The procedure for the wavelet de-noising of a roughness profile consists of several steps as shown in Fig. 1. The first step is the decomposition, which can be done by the discrete wavelet transform or by the wavelet packet method. The actual de-noising is performed by applying a threshold to the high-frequency components. The value of the threshold depends on an estimation of the level of noise in the data and the threshold selection method. The application of the threshold can also be done in the hard as well as soft mode. The final step involves the reconstruction of the thresholded components to yield the de-noised profile. The following sections provide a more detailed description of the wavelet de-noising procedure.

3.1 Wavelet decomposition and reconstruction

The wavelet decomposition process consists of two operations: filtering and downsampling. Filtering separates the signal into components of different scale: convolution with a low-pass filter generates the low-frequency components known as approximation coefficients, and convolution with a high-pass filter results in the high frequency components known as detail coefficients. The downsampling operation reduces the resolution of the coefficients to one-half. The decomposition process may be iterated in several levels. In multi-level decomposition we distinguish between two decomposition principles. In the discrete wavelet transform (DWT), the decomposition is applied to approximation coefficients only. In the wavelet packet method (WP) both the approximations and the details are decomposed.

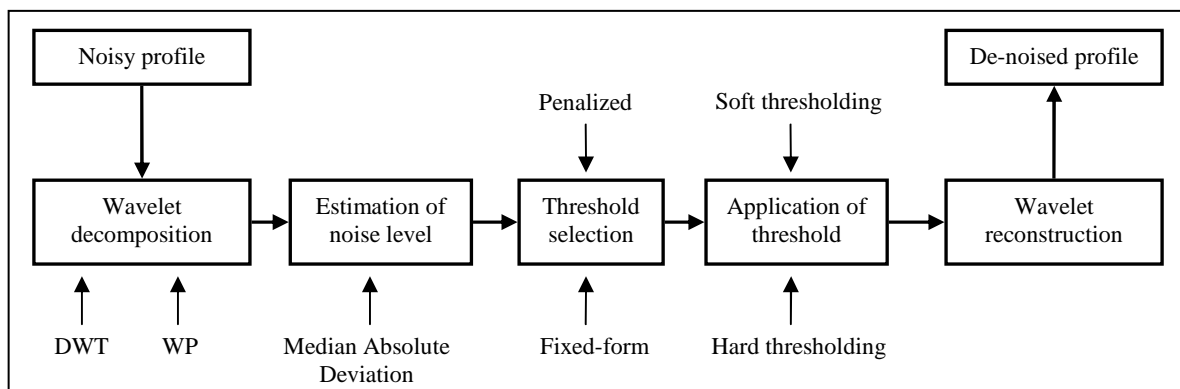


Fig. 1. Wavelet de-noising procedure.

Wavelet reconstruction is the process of recovering the original profile from its components. The reconstruction process consists of two operations: upsampling and filtering. The components are upsampled by inserting zeros between the samples and then convolved with the reconstruction filters. The approximation coefficients are convolved with a dual low-pass filter, and the detail coefficients are convolved with a dual high-pass filter. The reconstructed approximations and details are then summed up to yield the reconstructed profile. The decomposition and reconstruction filters should meet certain requirements in order to guarantee a perfect reconstruction of the data from the coefficients. A detailed description of the design of wavelet filters can be found in Strang and Nguyen (1996).

3.2 Thresholding of wavelet coefficients

De-noising by the thresholding of wavelet coefficients is based on an important property of wavelet decomposition that transforms white noise into white noise (Donoho and Johnstone, 1995). Since normally systematic errors are eliminated from the laser scanner data it is prudent to assume that the remaining error is white noise with Gaussian distribution. The thresholding is usually applied to the detail coefficients to ensure the preservation of the actual data. There are several methods for the estimation of the threshold value. In this paper, we compare two main threshold estimation methods: fixed-form thresholding and penalized thresholding.

The fixed-form thresholding method was proposed by Donoho and Johnstone (1994). For the detail coefficients of a profile obtained by the discrete wavelet transform the fixed-form threshold is estimated as:

$$t^f = \sigma_n \sqrt{2 \log(d)} \quad (2)$$

where d is the length of the detail coefficients at the first level of decomposition, and σ_n is the standard deviation of noise. For the wavelet packet decomposition of a profile the fixed-form threshold is estimated as:

$$t^f = \sigma_n \sqrt{2 \log(d \log(d) / \log(2))} \quad (3)$$

To estimate the standard deviation of noise from the data the median absolute deviation (MAD) of the coefficients has been proposed by Donoho and Johnstone (1995):

$$\sigma_n = \frac{1}{0.6745} \text{Median}(|w_k|) \quad (4)$$

where w_k are the detail coefficients at the first level.

The penalized thresholding method was proposed by Birge and Massart (1997). This method is based on minimizing a penalty function defined as:

$$t^* = \arg \min_{t=1, \dots, n} \left[-\sum (w_k^2, k < t) + 2t\sigma_n^2 \left(\alpha + \log\left(\frac{n}{t}\right) \right) \right] \quad (5)$$

where α is a sparsity parameter and n is the number of detail coefficients w_k sorted in descending order. The penalized threshold for both the discrete wavelet transform and the wavelet packet is then estimated as:

$$t^p = |w_{t^*}| \quad (6)$$

The sparsity parameter α can be tuned to obtain different threshold values. Three levels of penalized thresholding are common: penalized low ($\alpha = 1.5$); penalized medium ($\alpha = 2$); and penalized high ($\alpha = 5$).

The application of the threshold can also be done in two modes. The standard hard thresholding criterion is defined as:

$$\hat{w}_{j,k}^h = \begin{cases} w_{j,k} & \text{if } |w_{j,k}| \geq t \\ 0 & \text{if } |w_{j,k}| < t \end{cases} \quad (7)$$

where t is the threshold and $w_{j,k}$ are wavelet coefficients. The soft thresholding criterion is defined as:

$$\hat{w}_{j,k}^s = \begin{cases} \text{sign}(w_{j,k}) (|w_{j,k}| - t) & \text{if } |w_{j,k}| \geq t \\ 0 & \text{if } |w_{j,k}| < t \end{cases} \quad (8)$$

The soft thresholding criterion for wavelet de-noising was suggested by Donoho (1995). In contrast to hard thresholding, which can result in discontinuities (sharp drops) in the de-noised profile, soft thresholding yields a smooth output. Fig. 2 demonstrates the difference between the hard and soft thresholding modes. In the hard thresholding mode data beyond the threshold are preserved, but discontinuities are inevitable. Soft thresholding on the other hand shrinks the entire profile in order to prevent the occurrence of discontinuities.

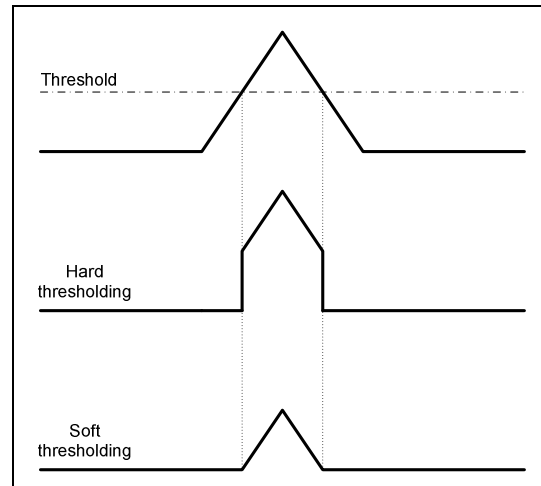


Fig. 2. The concept of hard and soft thresholding.

4. EXPERIMENTS AND RESULTS

The wavelet decomposition and thresholding methods were applied to roughness profiles extracted from a laser point cloud of a rock surface with millimeter-scale roughness. Fractal dimension was estimated for the de-noised profiles as well as the original laser profiles, and also for the manually measured roughness profiles to serve as reference. The following sections describe the experimental setup followed by the results and comparisons.

4.1 Study area

The scanned rock is situated in Tailfer, about 20 km south of the city of Namur and on the east side of the Meuse River in southern Belgium. The geological character of the scanned rock is a slightly metamorphosed limestone that is part of Lustin formation of carbonate mounts.

4.2 Data description

The rock surface was scanned with a Faro LS880 terrestrial laser scanner (Faro, 2009). The scanner was positioned at approximately 5 meters distance to the rock surface, and operated at the highest possible angular resolution, i.e. 0.009 degrees. The resulting point cloud contained about 1.2 million points on the rock surface with a point-spacing of 1 mm on average. According to the technical specifications of the laser scanner, the nominal range precision at a perpendicular incidence angle, which was roughly the case in our scan, is between 0.7 mm and 5.2 mm respectively for objects of 90% and 10% reflectivity at a distance of 10 m.

Roughness data were also collected manually along three profiles on the rock surface by using a carpenter's profile gauge with metallic rods at 1 mm intervals. These profiles were marked with white chalk and were visible in the reflectance image of the laser scanner data. Fig. 3 shows the profiles along which manual measurements were made, and their traces in the reflectance data of the point cloud.

The principal components were computed for a cutout of the point cloud that contained the profiles. The transformation parameters were then applied to rotate the point cloud into a more or less horizontal surface. Guided by the chalk traces in the reflectance image, three corresponding roughness profiles were extracted from the point cloud with samples interpolated at regular 1 mm intervals. The results of this procedure were three pairs of roughness profiles derived correspondingly from the manual and laser measurements with the same length and spatial resolution. We refer to these as the horizontal, diagonal and vertical profiles. Fig. 4 depicts the corresponding manual and laser roughness profiles in the horizontal direction.

4.3 Results

Using the roughness length method the fractal dimension was estimated for roughness profiles from both the laser scanner data and the manual measurements. The unit of profile length was chosen as 1 cm for all profiles to guarantee an appropriate density of 10 points per unit length. The power law relation was determined for each profile by calculating the standard deviation of the profile height within windows of 8 different sizes ranging from 3% to 10% of the profile length. Fig. 5 illustrates the power law relation between the window size and the standard deviation of the profile height for the laser and manual profiles in the horizontal direction. Here, the fractal dimension is estimated at 1.17 for the manual profile, and 1.96 for the laser profile. Considering the expected range of 1.2-1.7, the laser profile yields a clearly overestimated measure of roughness, while the fractal dimension of the manual profile is also slightly below the expected range.

To study the role of wavelet de-noising, different wavelet decomposition and thresholding methods were applied to the laser profiles and the estimated fractal dimensions for the de-noised profiles were compared with those of the manual profiles. For all profiles the decomposition was performed in 3 levels using a Daubechies wavelet of order 3 (db3). The standard deviation of noise was estimated at 1.8 mm, 1.3 mm, and 1.5 mm, respectively for the laser profile in the horizontal, diagonal and vertical direction. From these estimated noise levels thresholds were computed using the methods described in Section 3.2, and were applied to the detail coefficients globally at all decomposition levels. Table 1 summarizes the fractal dimensions estimated for the de-noised profiles obtained by using the discrete wavelet transform as the decomposition method. The same measures estimated for the de-noised profiles obtained by using the wavelet packets are summarized in Table 2. It can be seen that the fractal dimensions of the de-noised profiles vary across different thresholding methods; the variation is however smaller across different decomposition methods.

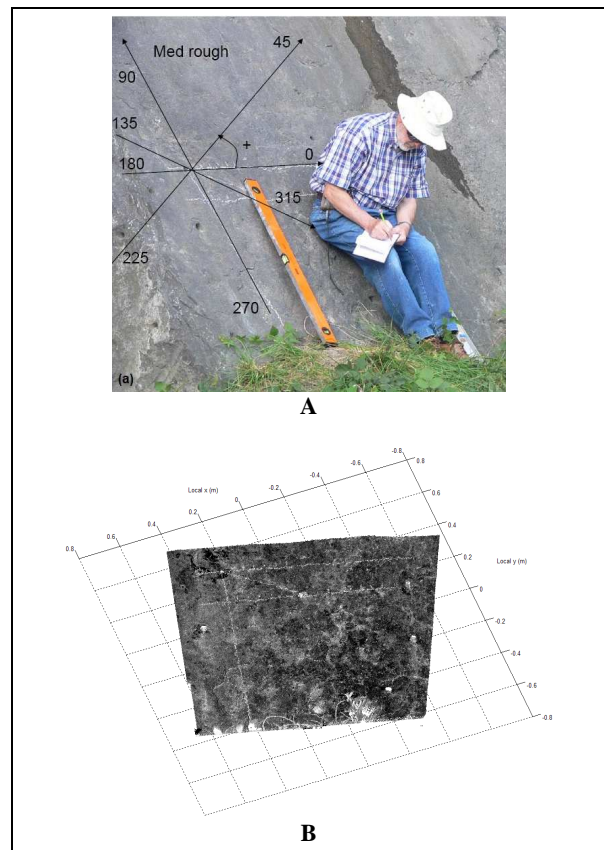


Fig. 3. A. manual measurement of roughness profiles; B. cutout of the rotated point cloud of the rock surface visualized with reflectance values.

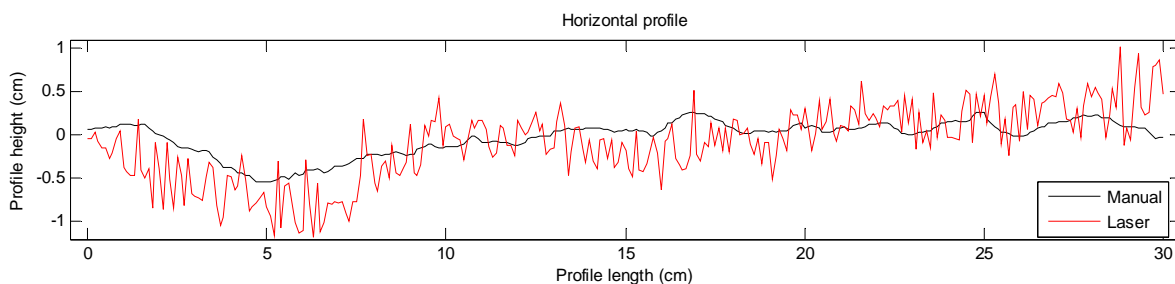


Fig. 4. Manually measured and laser scanned roughness profiles in the horizontal direction.

Fig. 6 depicts the variation in the fractal dimension of the de-noised profiles in the horizontal direction across different decomposition and thresholding methods. As it can be seen, the choice of the decomposition method has a minor impact on the fractal dimension of the de-noised profiles: the fractal dimensions pertaining to the discrete wavelet transform are only slightly larger than those of the wavelet packets. This can be verified also for the diagonal and vertical profiles from Table 1 and Table 2.

A noticeable difference in the performance of the de-noising methods can be seen in the application of hard and soft thresholding modes. Fig. 7 shows the influence of hard and soft thresholding on the fractal dimension obtained for the de-noised profiles in the horizontal direction. Soft thresholding results in too smooth de-noised profiles for which the estimated fractal dimensions are smaller than that of the manually measured profile and below the expected range. On the contrary, the de-noised profiles obtained by hard thresholding yield fractal dimensions that are within the expected range, except when penalized-high thresholding method is used. The fractal dimensions corresponding to the penalized high thresholding with both decomposition methods are in fact smaller than 1. The difference between the performances of hard and soft thresholding methods can be seen also for the diagonal and vertical profiles in Table 1 and Table 2.

An examination of the results of different thresholding methods suggests that the fixed-form threshold applied in hard mode to the coefficients obtained by the wavelet packet decomposition yields fractal dimension values that are closer to those of the manually measured profiles and are also within the expected range. With the discrete wavelet transform as the decomposition method the penalized low thresholding method applied in soft mode seems to be an appropriate choice. Fig. 8 shows the result of penalized-low soft thresholding applied to the DWT coefficients of the horizontal laser profile, which compares well with the corresponding manually measured profile.

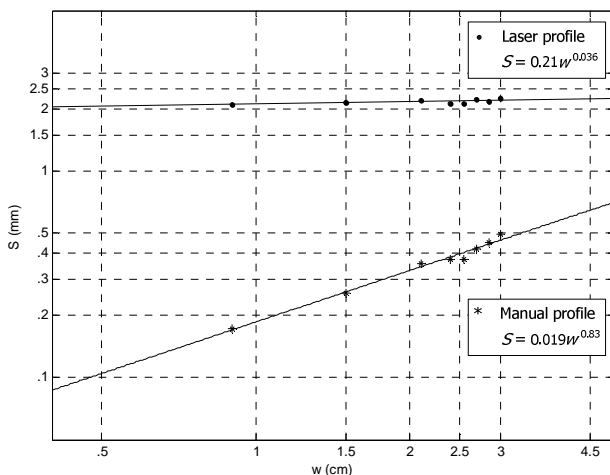


Fig. 5. The log-log plot of the standard deviation of profile height against window length for the laser and manually measured profiles in the horizontal direction.

5. CONCLUDING REMARKS

We investigated the role of wavelet de-noising of laser range data in reliable characterization of rock surface roughness. It

was shown that fractal dimension values estimated for profiles derived from laser scanner data are generally larger than the expected values. The role of wavelet de-noising was investigated through the comparison of fractal dimensions estimated for the de-noised profiles with those of the corresponding manually measured profiles. The results of wavelet de-noising methods in general led to an improvement of the roughness measures estimated for the laser profiles. The fractal dimensions obtained for most of the decomposition and thresholding methods were within the expected range. The choice of the decomposition method was not found to affect the de-noising result; however, the application of hard or soft thresholding mode did have an impact on the estimated roughness measures. The presented results suggest that hard thresholding yields more accurate de-noised profiles for which the estimated roughness measures are more reliable.

In this research, the de-noising methods were applied to 1D profiles extracted from the laser scanner point cloud. Future research will focus on 2D wavelet de-noising of a range image, which is the fundamental data structure of terrestrial laser scanners. Other topics for further research include an investigation of the role of point density and profile length, and an analysis of the de-noising results using other roughness characterization methods.

			Horiz. profile	Diag. profile	Vert. profile	
Original profile extracted from laser data			1.96	1.89	1.90	
De-noised profiles	Soft Thresh.	Fixed-form	1.05	1.23	0.81	
		Penalized	Low	1.23	1.38	1.19
			Med.	1.07	1.32	1.07
			High	0.94	1.19	0.62
Discrete Wavelet Transform	Hard Thresh.	Fixed-form	1.51	1.46	1.33	
		Penalized	Low	1.68	1.76	1.68
			Med.	1.51	1.69	1.59
			High	0.94	1.44	0.62
Manually measured profile			1.17	1.32	1.20	

Table 1. Fractal dimension values estimated for the de-noised profiles using discrete wavelet transform as the decomposition method.

			Horiz. profile	Diag. profile	Vert. profile	
Original profile extracted from laser data			1.96	1.89	1.90	
De-noised profiles	Soft Thresh.	Fixed-form	0.95	1.09	0.74	
		Penalized	Low	1.10	1.40	1.11
			Med.	1.10	1.26	0.95
			High	0.94	1.08	0.66
Wavelet Packets	Hard Thresh.	Fixed-form	1.42	1.38	1.30	
		Penalized	Low	1.52	1.79	1.66
			Med.	1.52	1.74	1.47
			High	0.94	1.19	1.18
Manually measured profile			1.17	1.32	1.20	

Table 2. Fractal dimension values estimated for the de-noised profiles using wavelet packets as the decomposition method.

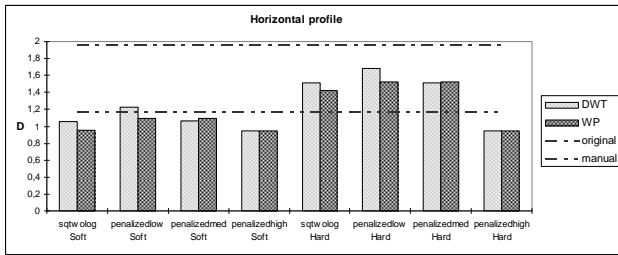


Fig. 6. Effect of decomposition method on the fractal dimension of de-noised profiles.

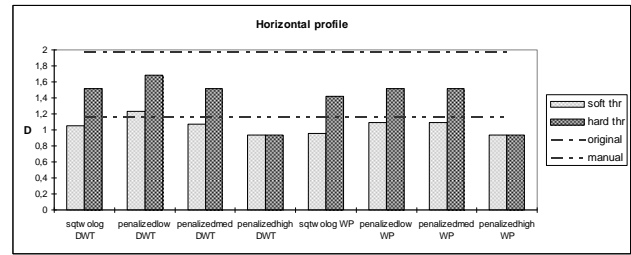


Fig. 7. Effect of hard and soft thresholding on the fractal dimension of de-noised profiles.

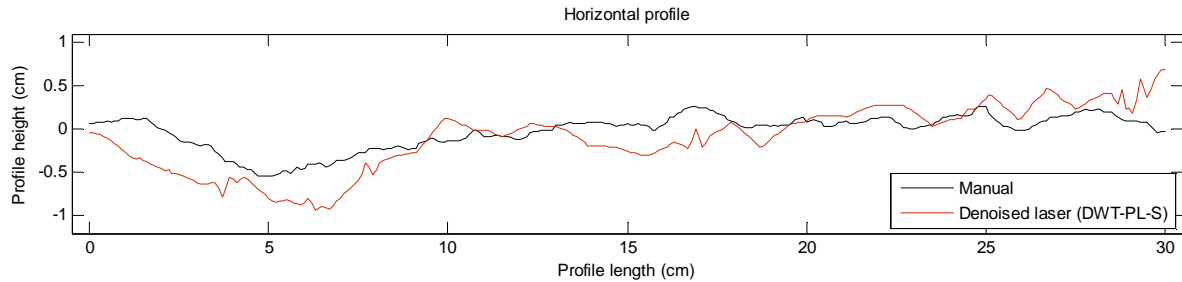


Fig. 8. De-noised laser profile obtained by penalized-low soft thresholding of the DWT coefficients compared with the corresponding manually measured profile.

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REFERENCES

Birgé, L. and Massart, P., 1997. From model selection to adaptive estimation. In: D. Pollard, E. Torgersen and G.L. Yang (Editors), *Festschrift for Lucien Le Cam: Research Papers in Probability and Statistics*. Springer-Verlag, New York.

Borah, D.K. and Voelz, D.G., 2007. Estimation of laser beam pointing parameters in the presence of atmospheric turbulence. *Applied Optics*, 46(23): 6010-6018.

Donoho, D.L., 1995. De-noising by soft-thresholding. *IEEE Transactions on Information Theory*, 41(3): 613-627.

Donoho, D.L. and Johnstone, I.M., 1994. Ideal spatial adaptation by wavelet shrinkage. *Biometrika*, 81(3): 425-455.

Donoho, D.L. and Johnstone, I.M., 1995. Adapting to unknown smoothness via wavelet shrinkage. *Journal of the American Statistical Association*, 90(432): 1200-1224.

Dorninger, P., Nothegger, C., Pfeifer, N. and Molnár, G., 2008. On-the-job detection and correction of systematic cyclic distance measurement errors of terrestrial laser scanners. *Journal of Applied Geodesy*, 2(4): 191-204.

Fardin, N., Feng, Q. and Stephansson, O., 2004. Application of a new in situ 3D laser scanner to study the scale effect on the rock joint surface roughness. *International Journal of Rock Mechanics and Mining Sciences*, 41(2): 329-335.

Faro, 2009. *Laser Scanner LS 880 Techsheet*, pp. Accessed September 2009 http://faro.com/FaroIP/Files/File/Techsheets%20Download/UK_LASER_SCANNER_LS.pdf.

Gonzalez, R.C. and Woods, R.E., 1992. *Digital image processing*. Addison-Wesley, New York, 716 pp.

Hardle, W., Kerkycharian, G., Picard, D. and Tsybakov, A., 1998. *Wavelets, approximation and statistical applications*. Lecture Notes in Statistics, 129. Springer Verlag, 254 pp.

Jolliffe, I.T., 2002. *Principal component analysis*. Springer, New York.

Kulatilake, P.H.S.W. and Um, J., 1999. Requirements for accurate quantification of self-affine roughness using the roughness-length method. *International Journal of Rock Mechanics and Mining Sciences*, 36(1): 5-18.

Lichti, D.D., 2007. Error modelling, calibration and analysis of an AM-CW terrestrial laser scanner system. *ISPRS Journal of Photogrammetry and Remote Sensing*, 61(5): 307-324.

Malinverno, A., 1990. A simple method to estimate the fractal dimension of a self-affine series. *Geophysical Research Letters*, 17(11): 1953-1956.

Rahman, Z., Slob, S. and Hack, R., 2006. Deriving roughness characteristics of rock mass discontinuities from terrestrial laser scan data, *Proceedings of 10th IAEG Congress: Engineering geology for tomorrow's cities*, Nottingham, United Kingdom.

Soudarissanane, S., Lindenbergh, R., Menenti, M. and Teunissen, P., 2009. Incidence angle influence on the quality of terrestrial laser scanning points, *ISPRS Workshop Laserscanning 2009*, Paris.

Strang, G. and Nguyen, T., 1996. *Wavelets and filter banks*. Wellesley-Cambridge Press, Wellesley MA USA, 490 pp.