Pavement Roughness Analysis Using Wavelet Theory

Liu Wei¹, T. F. Fwa² and Zhao Zhe³
¹Research Scholar; ²Professor; ³Research Student
Center for Transportation Research
Dept of Civil Engineering
National University of Singapore

SYNOPSIS

Road roughness has long been used as one of the primary indicator of pavement condition. It is today a common practice in pavement engineering to measure longitudinal pavement roughness and compute a suitable roughness index as an estimate of pavement serviceability performance. With the development of high-speed profilometers, vast data of road surface profile has been obtained that need to be processed. Road roughness is normally characterized by a summary index that applies over a length of road. Summary index measures are obtained most directly by measuring the longitudinal profile and then applying a mathematical analysis to reduce the profile to the roughness statistic. Existing options include calculating the International Roughness Index (IRI), Root Mean Square Vertical Acceleration (RMSVA), and Slope Variance (SV) values.

However, all of these summary indices can only give an average condition for a relatively long section of pavement and do not retain the actual contents of pavement surface roughness. Such detailed roughness contents information may be useful for maintenance operations, diagnosis of surface roughness as a defect, and detailed analysis of the trend of pavement performance deterioration. This paper presents a wavelet transform analysis procedure to offer supplementary information to the commonly used road indices. The proposed wavelet analysis is able to provide useful information for network pavement management and pavement maintenance operations. It can be a valuable tool for highway engineers, as a supplement to the IRI (or other roughness indices) analysis, to gain more insight into the behavior and performance of highway pavement under their charge.

Based on the analyses presented in this paper and the information derived thereof, the following conclusions may be made: (a) Road roughness profiles can be decomposed into different frequency subbands by applying DWT. Each frequency subband represents a certain range of wavelengths of road surface roughness. For normal roughness records with data points in intervals of 152mm (6in), the use of the following frequency subbands have been found to produce sufficient details for road roughness analysis: 0-0.11cycle/m for d₅, 0.11-0.21cycle/m for d₆, 0.21-0.41cycle/m for d₇, 0.41-0.82cycle/m for d₈, 0.82-1.64cycle/m for d₉, and 1.64-3.28cycle/m for d₁. The corresponding ranges of wavelength are 9.6m or more for d₅, 4.8-9.6m for d₆, 2.4-4.8m for d₇, 1.2-2.4m for d₈, 0.6-1.2m for d₉ and 0.3-0.6m for d₁; (b) Both DWT and CWT can detect the presence of local irregularities in the roughness profile analyzed. The wavelet analysis can detect the sharp magnitude change in the roughness profile as well as the location where the particular irregularity occurs. Examples given in the paper indicate that this wavelet analysis procedure can be successfully applied to detect surface distresses such as raveling, depressions, settlement, potholes or surface heaving in asphalt pavement surface and to detect joint faulting in cement concrete pavement surface; (c) Both CWT and wavelet based PSD can be applied to monitor the roughness deterioration of pavement sections. The 3-dimensional plots by CWT analysis provide an excellent visual appreciation of the changes in roughness contents in the pavement section concerned. It can serve as an assistant tool for monitoring road condition in pavement management system. The wavelet based PSD is smoother compared to Fourier based PSD which makes it more simple and accurate to use in characterizing road roughness features.

INTRODUCTION

A road roughness profile is a vertical section along the wheel track that shows the elevation of the surface as a function of the distance traveled. Road roughness is defined as the road surface irregularities in the longitudinal profile that influence the motion and operation of a moving vehicle through their effect on the user’s perception of
ride quality. Road roughness assessment is gaining increasing importance in pavement management system (PMS) as an indicator of road condition, both in terms of road pavement performance, and as a major determinant of road user costs.

Road roughness is normally characterized by a summary index that applies over a length of road. Summary index measures are obtained most directly by measuring the longitudinal profile and then applying a mathematical analysis to reduce the profile to the roughness statistic. Many studies, including the International Roughness Index (Sayers 1986), Root Mean Square Vertical Acceleration (Husden 1985), Slope Variance (Carey and Huckins 1962) values, have been conducted to find the road surface indices that are the most relevant explanatory variables in road roughness serviceability prediction models and, consequently, from which road maintenance and rehabilitation work can be planned. However, summary indices are obtained from post-processing of the roadway profile data and is a summary of thousands of elevation points. Therefore, it can only provide an average condition for relatively long sections of pavement. It is not sufficient enough to tell where or what the problems are. The development of high-speed profilometer makes it possible to record sampled road profiles with enough accuracy. The roughness profile provides another dimension to the description of roughness, showing with maximum detail how the roughness is distributed over the length of the road. A complete road roughness profile consists of all features ranging from hills and valleys down to surface texture.

The surface deviations in the longitudinal profile of a road pavement are random in nature, but they can be characterized by a combination of waveforms of various amplitudes and wavelengths. The full spectrum of roughness amplitudes can be represented by the displacement power spectral density (PSD) as a function of the wavenumber (the inverse of the wavelength) (Sayers et al 1986). The ISO 8608 standard (ISO 1995) was developed to provide standardized methods of comparing vertical road profile measurements based on results of PSD function of the profile data. To obtain a good estimate of the PSD, it is necessary to have a reasonably long sample. The ISO standard in fact specifies that the sections should be at least 1km long. Thus the ISO methods are aimed at describing the average condition of the pavement. However, according to studies conducted in France and Portugal (Delanne and Pereira 2000), PSD was not considered a reliable reference for serviceability evaluation. Furthermore, calculating the profile PSD as is done in the ISO standard eliminates all spatial information from the data. Therefore, it is not possible to pinpoint local defects from the PSD distribution. Moreover, these data must correspond to a stationary series (Priestley 1981). If this assumption is not verified, nonstationary signal-processing methods must be applied.

The wavelet transform or wavelet analysis (Daubechies 1988, 1992) is an analytical tool developed relatively recently to overcome the shortcomings of the Fourier transform. Wavelets are functions that satisfy certain mathematical requirements and are used in representing data or other functions. The wavelet transform can be used to decompose a signal into different frequency components and then present each component with a resolution matched to its scale. In the end the result will be a collection of time and frequency representations of the signal in different resolutions. One major advantage afforded by wavelets analysis is the ability to perform local analysis — that is, to analyze a localized area of a larger signal. Therefore, wavelet analysis is capable of revealing aspects of data that other signal analysis techniques miss, aspects like trends, breakdown points, discontinuities in higher derivatives, and self-similarity. In road roughness analysis, it is able to reveal localized surface irregularities such as surface depressions, potholes, surface heaving and bumps.

This paper presents a wavelet transform analysis procedure to offer supplementary information to the commonly used road indices (such as the IRI and RMSVA), to provide further insight into the characteristics of the roughness profile of interest. The procedure is able to identify the characteristics of a pavement roughness profile in both frequency and distance domains. Numerical examples based on measured roughness profiles from LTPP (Long Term Pavement Performance) database (UMTRI 1998) are presented. It is demonstrated that using this procedure, detailed roughness features of interest to pavement engineers not currently available from summary roughness indices can be obtained, which can be useful for pavement maintenance and rehabilitation planning in pavement management system (PMS).

THEORY OF WAVELET ANALYSIS

Overview of Wavelet Analysis
Wavelet analysis is a recently developed mathematical tool for signal analysis. Its primary applications have been in the areas of signal processing, image compression, subband coding, and sound synthesis. The
The fundamental idea behind wavelet analysis is to use wavelet functions that satisfy certain mathematical requirements to represent data or other functions.

The most well-known signal analysis tool is Fourier analysis which relies on a single basis function. Fourier transform breaks down a signal into constituent sinusoids of different frequencies. Its popularity is because of its ability to analyze a signal in the time domain for its frequency content. However it has several limitations. One major limitation is that in transforming the signal to the frequency domain, time information is lost. Researchers have attempted to correct these deficiencies over the years through short-time-Fourier transforms (STFT) and Gabor transforms. STFT uses a window function and translates it in time to split the signal into locally stationary fractions of the signal before performing Fourier transforms on each of these parts. It has the disadvantage that the window size is fixed. Wavelet transforms provide a way to overcome this problem.

The wavelet transform uses short width windows at high frequencies and long width windows at low frequencies. Wavelet transforms have an infinite set of possible basis functions as opposed to Fourier transform which uses the single set of basis functions. Also the computation time is of O(n) where Fourier transform is of order O(n*log2(n)).

**Mother Wavelet and Wavelet Functions**

The wavelet analysis procedure begins with the adoption of a wavelet prototype function, called an analyzing wavelet or mother wavelet. The mother wavelet processes the properties of square integrability, and is orthonormal in her translations and dilations. There are many kinds of mother wavelets. One can choose between smooth wavelets, wavelets with simple mathematical expressions, wavelets with simple associated filters, compactly supported wavelets, etc (Daubechies 1992). In the present studies, the wavelet functions developed by Daubechies were considered. The Daubechies family of wavelet DB1 to DB10 was analyzed. The number n in the Duabechies family code DBn is related to the smoothness of the wavelet. Wavelets with rapid changing features have small n values (e.g. smaller than 3) and vice versa. The wavelet DB3 (see Fig. 1) was selected as the mother wavelet in present analysis as the results based on this can provide adequate resolution in both the frequency and distance domains.

The mother function can be used to generate a whole family of wavelets by translating and scaling the mother wavelet (see Equation 1)

\[
\psi_{a,b}(x) = \frac{1}{\sqrt{|a|}} \psi\left(\frac{x-b}{a}\right)
\]  

(1)

Here b is the translation parameter and a is the scaling parameter.

**Continuous Wavelet Transform**

The Continuous Wavelet Transform (CWT) is similar to the Fourier Transform (FT), except that instead of a basis of infinite sines and cosines of different frequencies, the CWT compares the signal with dilated and time-shifted versions of a single basis function called the mother wavelet. The definition of the CWT is:

\[
W(a,b) = \int_{-\infty}^{\infty} s(t) \frac{1}{\sqrt{|a|}} \psi\left(\frac{t-b}{a}\right) dt
\]  

(2)

where s(t) can be any time dependent signal, \(\psi(t)\) is the mother wavelet, a is the dilation (or scale) of the mother wavelet and b is the time-shift (or translation) of the wavelet with respect to the signal and W(a,b) is the computed wavelet coefficient at scale a and position b. The factor \(1/\sqrt{|a|}\) is included to ensure that all the scaled wavelet functions have the same energy.

The time and frequency resolutions of the CWT depend on the scale. At high frequencies (low scale), the resolution in time is good, but the resolution in frequency is poor. This is due to the fact that the analyzing wavelet in well localized in time, but poorly localized in frequency. At low frequencies (high scale), the frequency resolution is good and the time resolution poor. This means that for a signal with rapid changes in frequency at high frequencies and slow changes in frequency at low frequencies, the results will give a better time frequency representation of the signal than the FT.
Discrete Wavelet Transform

Just as a discrete Fourier transform can be derived from Fourier transform, so can a Discrete Wavelet Transform (DWT) be derived from a continuous wavelet transform. The scales and positions are discretized based on powers of two while the signal is also discretized. The resulting expression is shown in Equation 3. The DWT can be easily and quickly implemented by filter bank techniques if the coefficients are thought of as a filter.

\[ W(i, j) = \sum_{n=0}^{N-1} s(n)2^{-j/2} \psi(2^j n - i) \]  

where \( i, j \) and \( n \) are integers and \( W(i, j) \) is the computed wavelet coefficient at level \( j \) and position \( i \).

Mallat developed in 1989 an efficient and practical filtering algorithm (Mallat 1989) to do the DWT. In the pyramidal algorithm, the original profile \( f(t) \) is first decomposed into a coarse (i.e. low frequency) component \( a_1 \) and a detailed component \( d_1 \). This process is repeated to further decompose the coarse component. That is, a coarse component \( a_j \) is decomposed into \( a_{j+1} \) and \( d_{j+1} \), where \( a_{j+1} \) is the lower frequency component of \( a_j \) and \( d_{j+1} \) is the higher frequency component of \( a_j \). This decomposition process is mathematically represented as follows,

\[ a_j(k) = \sum_{i=1}^{N} h_j(2k - i)s(i) \quad j = 1, 2, \ldots, L \]  

And

\[ d_j(k) = \sum_{i=1}^{N} g_j(2k - i)s(i) \quad j = 1, 2, \ldots, L \]  

where \( L \) is the total number of level of decomposition, \( k = 1, 2, \ldots, n \), \( a_j \) the low frequency component of the level \( j \), \( d_j \) the high frequency component of the level \( j \), \( h_j \) the low-pass filter of level \( j \), and \( g_j \) the high-pass filter of level \( j \). The original signal can thus be represented as the sum of a series of signals as follows:

\[ s = a_L(n) + \sum_{j=1}^{L} d_j(n) \]  

Thanks to Mallat’s work, wavelets became much easier. One could now do a wavelet analysis without knowing the formula for a mother wavelet. The language of wavelets also became more comfortable to engineers, who embraced familiar terms such as “filters,” “high frequencies,” and “low frequencies.”
Wavelet-Based Energy and Power Spectra

The total energy contained in a signal, $x(t)$, is defined as its integrated squared magnitude as follows:

$$E = \int_{-\infty}^{\infty} |x(t)|^2 \, dt$$

(7)

The relative contribution of the signal energy contained at a specific scale and location in the CWT is given by the two-dimensional wavelet energy density function:

$$E(a,b) = \|W(a,b)\|^2$$

(8)

A plot of $E(a,b)$ is known as a scalogram (analogous to the spectrogram, the energy density surface of the STFT). The scalogram can be integrated across $a$ and $b$ to recover the total energy in the signal as follows:

$$E = \frac{1}{C_g} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} E(a,b) \frac{db}{a^2}$$

(9)

where $C_g$ is the admissibility constant of the wavelet function $\psi(t)$.

The relative contribution to the total energy contained in the signal at a specific scale is given by the scale-dependent energy distribution:

$$E(a) = \frac{1}{C_g} \int_{-\infty}^{\infty} E(a,b) \, db$$

(10)

Peaks in $E(a)$ highlight the dominant energetic scales within the signal. We may convert the scale-dependent wavelet energy spectrum of the signal, $E(a)$, into a frequency-dependent wavelet energy spectrum $E_w(f)$ in order to compare directly with the Fourier energy spectrum of the signal $E_F(f)$, which is defined as the squared magnitude of the Fourier transform of the signal. To do this we must convert from the wavelet scale $a$ to a characteristic frequency of the wavelet. One of the most commonly used characteristic frequencies used in practice is the passband center of the wavelet’s power spectrum. Using this passband frequency, the characteristic frequency associated with a wavelet of arbitrary scale is given by

$$f = \frac{f_c}{a}$$

(11)

where $f_c$ is the passband center of the mother wavelet, which is equal to 0.8 for DB3 wavelet. According to the relationship given in Equation. 11, the frequency-dependent wavelet energy spectrum $E_w(f)$ is given by

$$E_w(f) = E(a) / f_c$$

(12)

In practice, experimental signals are usually of finite length. Hence, the power spectra are more often used to characterize experimental signals. The power spectrum is simply the energy spectrum divided by the time period of signal under investigation. Therefore, for a given signal of length $\tau$, the Fourier and wavelet power spectra are, respectively,

$$P_F(f) = \frac{1}{\tau} E_F(f)$$

(13)

$$P_w(f) = \frac{1}{\tau} E_w(f)$$

(14)

Due to the frequency distribution within each wavelet, the resulting wavelet power spectrum is smeared compared with the Fourier spectrum. However, the wavelet spectrum is more than simply a smeared version of the Fourier spectrum because the smoothing required by the ISO standard is implicit in the process.

WAVELET APPLICATIONS IN ROUGHNESS PROFILE ANALYSIS

Identifying Local Roughness Features

One major advantage afforded by wavelets analysis is the ability to perform local analysis — that is, to analyze a localized area of a larger signal. Therefore, wavelet analysis is capable of revealing aspects of data that other signal analysis techniques miss, aspects like trends, breakdown points, discontinuities in higher derivatives, and self-similarity. In road roughness analysis, wavelet analysis is able to detect from road roughness data the
occurrences and locations of localized surface caused by pavement distresses such as surface revalling, depressions, settlement, potholes, surface heaving and humps. When a data point in the road roughness profile record measured by a high-speed profilometer falls on one of these surface distress, it causes a relatively sharp change of surface elevation compared with the surface roughness profile recorded before and after it. This localized feature will appear in the signal of a decomposed high frequency sub-band obtained from wavelet analysis.

Fig.2 shows a road roughness profile of an LTPP asphalt pavement section GPS-1597 in Pennsylvania and its 6 frequency subbands obtained from Discrete Wavelet Transform (DWT). This roughness profile was chosen from LTPP database and its IRI value is 2.51m/km. According to this IRI value, we can tell that the ride-ability of this section was not very good. Some surface defects may exist in this section. But we cannot tell where the problems are just based on IRI value. According to the DWT results, we can see that surface defects with relatively large wavelength (2.4m to 9.6m), which represent defects deriving from the pavement subgrade deformation, were detected by subband d4 and d5; surface defects with relatively small wavelength (0.6m-2.4m), which maybe result from defects in the upper pavement layers, were detected by subband d3, d2 and d1. Not only the position of these surface defects can be identified, the magnitudes of these defects can also obtained from the results shown in Fig.2.

Joint faulting is an important type of distresses in concrete pavement. When a joint faulting occurs, the elevation change between the 2 data points at the joints is expected to be larger than those elevation changes within the slab. This makes it possible to detect joint defects from road roughness profile. Wavelet transform is sensitive to those sudden changes in the profile and can detect them in its high frequency subband (e.g. d1). This makes it possible to detect joint defects from road roughness profile base on wavelet transform. An algorithm was developed to detect joint defect from road roughness profile for this purpose. Fig.3 shows an original profile of a concrete pavement surface, together with its frequency subband d1 obtained from DWT, possible joints locations obtained from DWT and the locations of possible joints on the profile. From Fig.3, the number of joints was detected as 33 and the average magnitude of joint faulting is calculated as 0.88mm. These results can also be found in LTPP database by site measurement. The number of joints was recorded as 33 and the average joint faulting was recorded as 0.8mm in LTPP database for this section. The comparison between LTPP database and present method indicates that present method is effective to detect joint faulting in concrete pavement from road roughness profile.

Monitoring Roughness Deterioration
Understanding the cause and the rate of pavement deterioration enables road authorities to carry out accurate remedies and use maintenance funds more effectively. The Continuous Wavelet Transform (CWT) is adopted for this purpose. The mode and extent of pavement deterioration can be monitored by tracking the result of CWT results of road roughness profiles over a period of years and examining the rate of roughness development in each scale.

The 6-year record of road section GPS-1597 Pennsylvania is used to conduct continuous wavelet transform. Fig. 4 gives the surface profile plots for the same test section in each of the 6 years. It can be observed the surface become rougher and the road section is expected to be under deterioration. Accordingly, the IRI records show an increase from 98.71 to 159.62. Fig.5 gives continuous wavelet transform of all the 6 profiles. It can be observed that the coefficients above scale 30 changes very little, corresponding to that the general shape of the profile does not vary much. However, at scale 0 to 30, we can see clearly rises of the coefficients of CWT year after year, indicating the profile is getting rougher. The transforms are with consistency to the profiles, and the spike-like components found in the profile can also be detected by the transform results. These results were also consistent with the results obtained from DWT in the previous section.

Characterizing Road Roughness Features by Wavelet Based Power Spectra
Like the Fourier-based PSD function, the wavelet based power spectra of the road surface profile can be obtained to characterizing features of different road roughness profile. In fact, because the wavelet transform provides both time (space) and frequency information, the wavelet based power spectra can be a two-dimensional plot. By averaging across the time (or space) axis, we can obtain a power vs. frequency function analogous to the Fourier-based PSD. Fig.6 shows the wavelet based PSD comparing to the Fourier-based PSD for the section of profile shown in Fig.2.
Fig. 2 Wavelet decomposition of road roughness profile into 6 frequency sub-bands
Fig. 3 Joint defects detection from roughness profile by DWT

(a) Original profile

(b) Detail sub-band $d_1$ of DWT

(c) Possible joint locations obtained from DWT

(d) Location of possible joints on the profile

Elevation (mm)

Distance (m)

Elevation (mm)

Distance (m)

Elevation (mm)

Distance (m)

Elevation (mm)

Distance (m)

Fig. 3 Joint defects detection from roughness profile by DWT
Fig. 4 Surface profile of pavement section GPS-1597 over 6 years
Fig. 5 3-dimensional plot of Continuous Wavelet Transform for Pennsylvania pavement section GPS-1597

(Year 1989) IRI = 1.50 (m/km)

(Year 1991) IRI = 1.65 (m/km)

(Year 1992) IRI = 1.74 (m/km)

(Year 1993) IRI = 1.79 (m/km)

(Year 1994) IRI = 2.16 (m/km)

(Year 1995) IRI = 2.43 (m/km)
In the previous section, the CWT was used to monitor the deterioration of road roughness. Similarly, the wavelet-based PSD can also be used to characterizing the deterioration of road roughness. Fig. 7 shows the results of wavelet base PSD for the road roughness profiles of pavement section GPS-1597 in Pennsylvania. The results show that the low frequency (wavenumber less than 0.5) components of road roughness changes little over years. However, the high frequency (wavenumber larger than 0.5) components changes very much over years which indicates that the roughness deterioration of this section primarily comes from the high frequency part. This results are also consistent with the observation from 3-dimensional plot of CWT.

CONCLUSIONS

The development of High-speed road profiling technology has led the International Road Roughness (IRI) become a standard indicator of road roughness. IRI has considerable merit as a summary profile-based roughness index. However, the profile data contain far more information about the condition of the surface, which can be extracted with other appropriate technique.

Over the past 10 years, wavelet transform analysis has become a powerful tool in the analysis and synthesis of signals and images. This paper presents a wavelet transform analysis procedure to offer supplementary information to the commonly used road roughness indices to provide further insight into the characteristics of the roughness profile of interest. Such additional information is currently not obtainable from summary indices such as the IRI and RMSVA.

Based on the analyses presented in this paper and the information derived thereof, the following conclusions may be made:

(a) Road roughness profiles can be decomposed into different frequency subbands by applying DWT. Each frequency subband represents a certain range of wavelengths of road surface roughness. For normal roughness records with data points in intervals of 152mm (6in), the use of the following frequency subbands have been found to produce sufficient details for road roughness analysis: 0-0.11cycle/m for \( a_5 \), 0.11-0.21cycle/m for \( d_5 \), 0.21-0.41cycle/m for \( d_4 \), 0.41-0.82 cycle/m for \( d_3 \), 0.82-1.64cycle/m for \( d_2 \), and 1.64-3.28cycle/m for \( d_1 \). The corresponding ranges of wavelength are 9.6m or more for \( a_5 \), 4.8-9.6m for \( d_5 \), 2.4-4.8m for \( d_4 \), 1.2-2.4m for \( d_3 \), 0.6-1.2m for \( d_2 \) and 0.3-0.6m for \( d_1 \).

(b) Both DWT and CWT can detect the presence of local irregularities in the roughness profile analyzed. The wavelet analysis can detect the sharp magnitude change in the roughness profile as well as the location where the particular irregularity occurs. Examples given in the paper indicate that this wavelet analysis procedure can be successfully applied to detect surface distresses such as raveling, depressions, settlement, potholes or surface heaving in asphalt pavement surface and to detect joint faulting in cement concrete pavement surface.

(c) Both CWT and wavelet based PSD can be applied to monitor the roughness deterioration of pavement sections. The 3-dimensional plots by CWT analysis provide an excellent visual appreciation of the changes in roughness contents in the pavement section concerned. It can serve as an assistant tool for monitoring road condition in pavement management system. The wavelet based PSD is smoother compared to Fourier based PSD which makes it more simple and accurate to use in characterizing road roughness features.

In summary, the proposed wavelet analysis is able to provide useful information for network pavement management and pavement maintenance operations. It can be a valuable tool for highway engineers, as a supplement to the IRI (or other roughness indices) analysis, to gain more insight into the behavior and performance of highway pavement under their charge.
Fig. 6 Comparison of Fourier-based PSD and Wavelet-based PSD

Fig. 7 Results of Wavelet based PSD for multi-year roughness profile of Pennsylvania pavement section GPS-1597
REFERENCES