Original research paper

# Vehicular emission approximation using wavelet analysis

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**Abstract**

Vehicular emission has been recognized as one of the major sources of air pollution as such emissions contain harmful greenhouse gases. Hence processing of air pollution data has gained interest which, in turn, made decomposition and transformation algorithms to be important tools in data analyses. For analyzing vehicular pollution, the key variables are the speed, acceleration and pavement roughness. Presently, portable emission measurement system (PEMS) can be employed to collect on-road gas emission data for every second and smartphone apps such as Roadroid are used to estimate road roughness. Although analytical modeling can provide average estimation on the behavior of roughness and how it affects the emission, numerical transformation and decomposition can offer superior approximation since these techniques sweep the whole spectrum of available data. This paper presents a discrete wavelet transformation procedure and discusses the low frequency components of the analysis to approximate the relation

between pavement roughness and gas emissions. Here, PEMS data of several road segments from greater Houston were considered. These road segments, selected as testing sites, are approximately 550 km of length in total. The emission data obtained from PEMS in these sites for various gas exhaust such as $CO_2$, CO, $NO_x$, and HC and fuel consumption (FC) are decomposed by Multilevel 1-dimensional discrete wavelet analysis to analyze the wavelet approximations of emission and the underlying trends. The results of this literature can assist in the prediction of vehicular emission for different pavement conditions.

**Keywords:**

Discrete wavelet transformation, approximation analysis, wavelet decomposition, pavement roughness, vehicular emission

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## 1 Introduction

Vehicular emission is one of the major contributors to air pollution and, thus, a risk for human health as well as for the environment. According to the National- Level Greenhouse Gas Inventory of EPA (2016), transportation sector is accounted to be the second largest portion of U.S. greenhouse gas emissions in 2014 contributing 26% to it. A report from the Massachusetts Institute of Technology's (MIT) Laboratory for Aviation and the Environment in 2013 presents that every year in the USA 53,000 early deaths occur due to vehicle pollutants (Caiazzo 2003). Carbon dioxide (CO2), carbon monoxide (CO), nitrogen oxides ($NO_x$), hydrocarbons (HC) etc. are the most malevolent gasses emitted by vehicles while in use. Identifying the causes that trigger the vehicular emissions and then modelling the emission to estimate accurately for planning emission control is necessary as they pose high risk to the environment and longer also, human health (Li 2015).

The several factors that could be responsible for influencing the type and amount of gas emissions on the road are vehicle type, ambient temperature, vehicle age, fuel type, and vehicle speed. Nabi et al. (2016) showed that activities such as changing lanes may have impact on vehicular emission and fuel consumption. But there could be another factor, pavement roughness, affecting vehicle speed and acceleration. Although speed and acceleration directly affect emissions, it is generally assumed that roadway pavement roughness might not directly affect gas emission rates as much as speed and acceleration, but the combined effect might be highly notable. Thus, studies have been conducted to explore the effect of road roughness on vehicular emission. One study indicated a slight decrease in the $CO_2$ emission from roads in poor conditions to roads in either fair or good condition (Kalembo 2012). Another study from Greene, Suzanne et al (2013) revealed a linear increase of fuel consumption with respect to roughness index for different types of vehicles. Both researches suggested that driving on rough roads consumes more fuel and produces more vehicular emission than driving on smooth roads. In order to assess its impact, the international roughness index (IRI) was invented as a common index for profile measurements of the road surface. It measures roughness that is based on the simulated response of a generic motor vehicle to the roughness in a single-wheel path of the road surface. The IRI was developed by the World Bank in the 1980s and has been identified as a primary factor to indicate

64 the condition of pavement (Papageorgiou 2014).

65 Portable emission measurement system (PEMS) is one of the most common and effective methods to
66 collect on-road emission data. The PEMS can measure emissions from an engine's combustion so that
67 the real-world in-use testing condition can be identified. It accurately measures gas emissions such as
68 $CO_2$, CO, $NO_x$, and HC as well as fuel consumption for each second while the vehicle or the equipment
69 are in use.

70 Wavelet transform or wavelet analysis is a very useful mathematical tool for frequency analysis as it
71 has overcome the limitations of Fourier transform. Wavelets are a type of function that is used for
72 confining a given function in both position and scaling (Veitch 2005). Fundamentally, the wavelet
73 transform can decompose a signal into several frequency features and then presents each of them with
74 a product matched to its scale (Wei 2002). It has been used widely in various other fields involving
75 computation such as computing, biology, and statistics especially for signal processing, image
76 compression, subband coding, and sound synthesis. However, several recent studies have been
77 successfully utilized this tool in the area of transportation research as it is proficient of analyzing
78 complicated mathematical function. Wei et al. (2005) suggested that wavelet analysis can present
79 detailed information of road roughness that is useful to maintenance operations, detection of pavement
80 surface deterioration, and the trend of roughness deterioration. Another research of Wei et al. (2004)
81 showed that wavelet transform can characterize detailed features of pavement roughness of different
82 wavelengths quantitatively with regard to wavelet energy. Zhao et al. (2006) proposed a wavelet-based distress
83 detection, isolation and evaluation which can be a useful index for pavement inspection and distress evaluation. In
84 an advanced research, Wang et al. (2014) developed a model incorporating wavelet neural network and genetic
85 algorithm that can predict the distribution of air pollution in real-time near road intersections. This research is
86 motivated by these previous studies where transformation techniques such as wavelet analysis were employed in
87 the field of pavement studies, whereas we intend to use it to reveal the complicated relation between pavement
88 roughness and vehicular emission.

89 **2 Research Objective**

90 The goal of this research is to evaluate the relationship between pavement roughness and vehicular

emission through performing multilevel discrete wavelet analysis on the gas emission and fuel consumption data collected during test drive. The results will be later validated by comparing with another curvilinear analysis. During wavelet analysis and subsequent sections, each type of emission data for all the road segments will be sorted according to the ranges of VSP (vehicle specific power) and then decomposed individually in order to be analyzed based on the approximations. Successful outlining of the dependency of vehicular emission on pavement roughness and its validation are expected to be the outcome of this analysis. These findings can be utilized later for roadway designing and planning to decrease vehicular emissions due to roughness.

## 3 Wavelet Transformation

Wavelet transform or analysis is the study on how a particular function is varying over time by finding a suitable wavelet function that matches with the given function with the variation of scales and position (Qiao 2003). The wavelet transform can be divided into two types: continuous wavelet transform (CWT) and discrete wavelet transform (DWT) based on whether the scale can be continuously taken or in a discrete manner.

Each wavelet is derived from a function ψ, which is generally referred to as the “mother wavelet” from two linear transformations that determine the width of the window and hence define the resolution of the transform as given in Eq. (1) (Daubechies 1992).

$$\psi_{s,u}(x) = \frac{1}{\sqrt{s}}.\psi\left(\frac{x-u}{s}\right) \tag{1}$$

where, *s* and *u* are scale parameters for dilation and translation, correspondingly.

The wavelet transform of a function f (x) for a given resolution (s, u) is then given as Eq. (2) (Daubechies 1992).

$$WT_{s,u}\{f(x)\} = \int_{-\infty}^{+\infty} f(x).\frac{1}{\sqrt{s}}.\psi^{T}\left(\frac{x-u}{s}\right)\,dx \tag{2}$$

### *3.1 One-Dimensional Discrete Wavelet Analysis*

There is one independent variable and one corresponding dependent variable in 1D wavelet analysis. It is effective to calculate wavelet coefficients of the dependent variable by choosing a subset of scales and positions of the independent variable rather than at every possible scale, which would, in turn, produce a huge amount of data (Qiao 2006). This analysis can be obtained from the discrete wavelet transform (DWT). In DWT, there are two relative terms: “approximations” and “details.” The “approximations” are the high-scale, low-frequency components of the signal, while the “details” are the low-scale, high-frequency components.

The decomposition process can be iterated, with successive approximations being decomposed in turn, so that one signal is broken down into many lower resolution components. This is called the wavelet decomposition tree. For example, a 1D signal s[n] is passed through a series of stages consisting of one high-pass and one low-pass filters in order to realize 1D-DWT. During each stage (also known as levels), the filter outputs are subsampled by 2. The process is shown in Fig 1. Where, $A_1$ and $D_1$ denote impulse functions through Level 1 low- and high-pass filters, respectively.

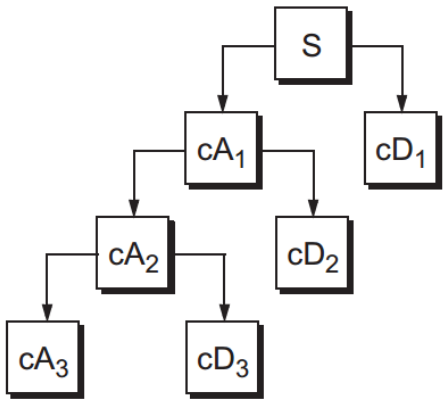



**Fig. 1** Wavelet Decomposition Tree

We can continue this process for further levels shown in Eq. (3).

$$\sum_{k=-\infty}^{\infty} s[k]a_1[2n-k] = A_1[n] \xrightarrow{Level\ 2} \sum_{k=-\infty}^{\infty} A_1[k]a_2[2^2n-k] + \sum_{k=-\infty}^{\infty} A_1[k]d_2[2^2n-k] \quad (3)$$

This process can be repeated for level m, and we will have one “approximation” signal $A_m$ along with

m-numbers of “details” signals, namely, $D_m$, $D_{(m-1)}$ ,$D_{(m-2)}$,……,$D_2$,$D_1$. As shown, the decomposition process can be iterated, with successive approximations being decomposed in turn, so that one signal s[n] is broken down into m+1 lower-resolution components. These components are then analyzed to reveal the nature and characteristics of the original signal.

## 4 Test Description

Several road segments of different length were selected to collect on-road data in greater Houston and are 422.66 km of length in total. The selected pavements are asphalt and were due to be treated at the time of test. The testing period was from May 1, 2015, to June 11, 2015, for the period of nonpeak hours during dry weather conditions (Average temperature was 84℉ with an average humidity of 68%). To maintain the integrity in driving behavior and pattern and also similar outputs of vehicular activities, one dedicated driver and vehicle were in service to conduct all the field tests. The vehicle was a light-duty gasoline vehicle: a 2004 Subaru Forester.

The PEMS was installed inside the vehicle and connected to the engine through three types of sensors: temperature, air-pressure, and RPM (Rotation Per Minute) sensors. When the vehicle was in use, the PEMS accurately recorded time, RPM, intake air temperature, air pressure, emission concentrations of $CO_2$, CO, HC, and $NO_x$ and speed for every second. Also, coordinates (latitude, longitude, and altitude) of the location for each second were obtained using Global Positioning System (GPS). An Android app called Roadroid was used to measure the roughness of the road the vehicle was driven on. Roadroid provides IRI data obtained by smartphone accelerometer and GPS-photo of the road, which is later highly correlated with the roughness measured by the Laser IRI surveys (Forslöf 2013). Then the app server wirelessly transfers the collected data to an internet mapping server with spatial filtering functions which makes the datasets highly reliable. A cell-phone with that app installed was mounted in the front of the vehicle, and the app was turned on the entire time of testing. The Roadroid can provide two options of IRI: a) estimated IRI (eIRI) and b) calculated IRI (cIRI) (Forslöf 2015).

## 5 Data Processing

PEMS produces data for $CO_2$, CO, $NO_x$, and HC and fuel consumption in time dependent manner such as gram/second or milligram/second whereas the IRI data are in the space domain (m/km). Therefore, the emission rates obtained directly from the PEMS were converted into emission factors (gram/meter or milligram/meter) for every 5 meter. Roadroid provides two types of IRI data: a) estimated IRI (eIRI) and b) calculated IRI (cIRI). The setup for eIRI is assumed to compensate for speed in a relatively larger range (20-100 km/hr) than cIRI which can accommodate narrower speed range such as 60-80 km/hr. The value of eIRI shows more consistency considering this factor and therefore, was used in this analysis. Vehicle specific power (VSP) is a function of speed and acceleration rate which was estimated from the instantaneous speed data acquired from PEMS. VSP for light duty vehicles was estimated by using the Eq. (4), as proposed by Jimenez–Palacios et al. (1998).

$$VSP = v \times (1.1a + 9.81 \times grade\% + 0.132) + 0.000302v^3 \quad (4)$$

where, v is the vehicle speed (m/s), a is the acceleration (m/s2) and grade is the vehicle's vertical rise divided by slope length which can be assumed to be zero if the terrain is flat.

The data points were uniformly spaced for sampling to decompose. In addition, data were binned into four VSP ranges: VSP < 0, 0 < VSP < 10, 10 < VSP < 20 and VSP > 20, to reduce the number of independent variables. The emission versus roughness data for each VSP range were collected and then sorted and interpolated in uniform data points. Although the PEMS data contains a large variation of both VSP and roughness, it was found that, the acceptable range of VSP is no less than -10 and no more than 30. IRI data were interpolated within a range of 1 m/km to 3 m/km having an interval of 0.01 m/km per the spreading of data points. Next, multi-level discrete wavelet analysis was performed using built-in MATLAB functions. Among the various types of wavelets, haar, Daubechies of order N (dbN), and Symlets of order N (symN) possess the properties required for simple discrete wavelet analysis. Although, above mentioned three types of wavelets were applied initially to decompose the data set but finally, "sym4" was used due to the minimum error.

The analysis provides the approximations of level 2 for all the gasses and FC for all VSP ranges. For the sake of discussion, an example of wavelet analysis of level 4 is showed in Fig. 2. Here, the approximation is denoted by A4 and it shows follows the trend of the original data. Emission factors or rates can be predicted using the approximation and thus, identifying the cause of emission features and

finding a probable solution of such emission occurring due to uneven pavement. The level 4 analysis also provides four two high-frequency components and two other low-frequency components. These frequency subbands combined with percentage of energy associated with each subband can reveal the lead contributor behind vehicular emission on road (Khan 2017). Although, the level of the analysis can be further increased, but an excessive level will not be able to provide any additional information; rather it will only burden computational labor.

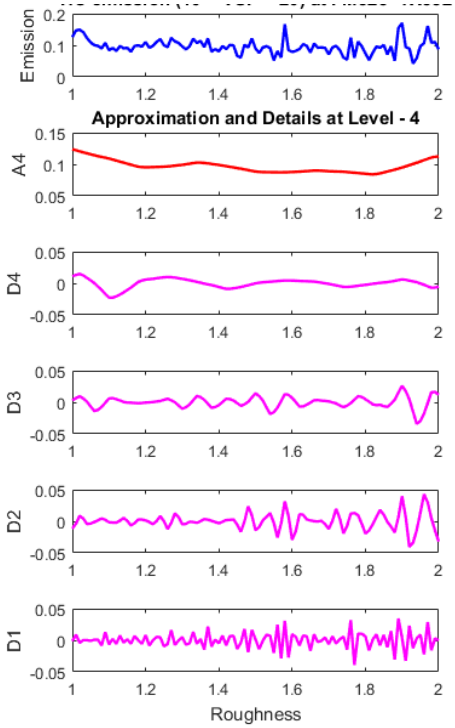



**Fig. 2** 1D discrete wavelet analysis to decompose one emission (mg/m) versus roughness (m/km) data

## 6 Result and Discussion

One major advantage offered by wavelets is the ability to perform local analysis—that is, to analyze a localized area of a larger signal due to its adaptive solving methods (Nagy 2015). Therefore, wavelet analysis is capable of revealing aspects of emission versus roughness data that other signal analysis techniques (such as Fourier Analysis) miss-aspects such as emission trends, breakdown points, and how emission changes for a small or large change of roughness. Furthermore, wavelet analysis inherently compresses large sets of data and is capable to de-noise a signal to reveal simplified approximations without degrading the signal itself. In this literature, the emission versus roughness data

for a particular range of VSP are decomposed and analyzed using 1D wavelet analysis.

### *6.1 Wavelet Analysis of Gas Emissions and Fuel Consumption versus Roughness*

As discussed above, the analysis on current data sample is limited in 2-level analysis for evaluating the approximations. This is because higher level of approximations will only lose data trend and thus, is detrimental for the purpose of this study. Now, multilevel 1D wavelet analysis is performed on $CO_2$, CO, HC, and $NO_x$ emission data collected from the selected road segments in order to decompose the data. Then the approximation is analyzed to understand the pattern and trend of the emissions and fuel consumption for each VSP range. The data for each emission were also fitted to Polynomial curvature of order 6. The Polyfit and Wavelet results were then compared to find out the best analysis.

Fig. 3 shows the comparison among original, wavelet and PolyFit data of $CO_2$ emission for the four different VSP ranges. The first sub-figure shows that the $CO_2$ emission has sharp peaks leading to 2 – 3 mg/m emission for negative VSP regime. For positive VSP, the maximum values of peaks are below 1 mg/m. It is evident from the figures that wavelet analysis is superior in approximating the experimental data than the polynomial fitting. While the polynomial fitting can only follow the general trend of the data, wavelet approximation captures the sudden rise and fall observed in PEMS data as well. This enables wavelet analysis to be a better candidate in approximating emission vs roughness trends for untested pavements.

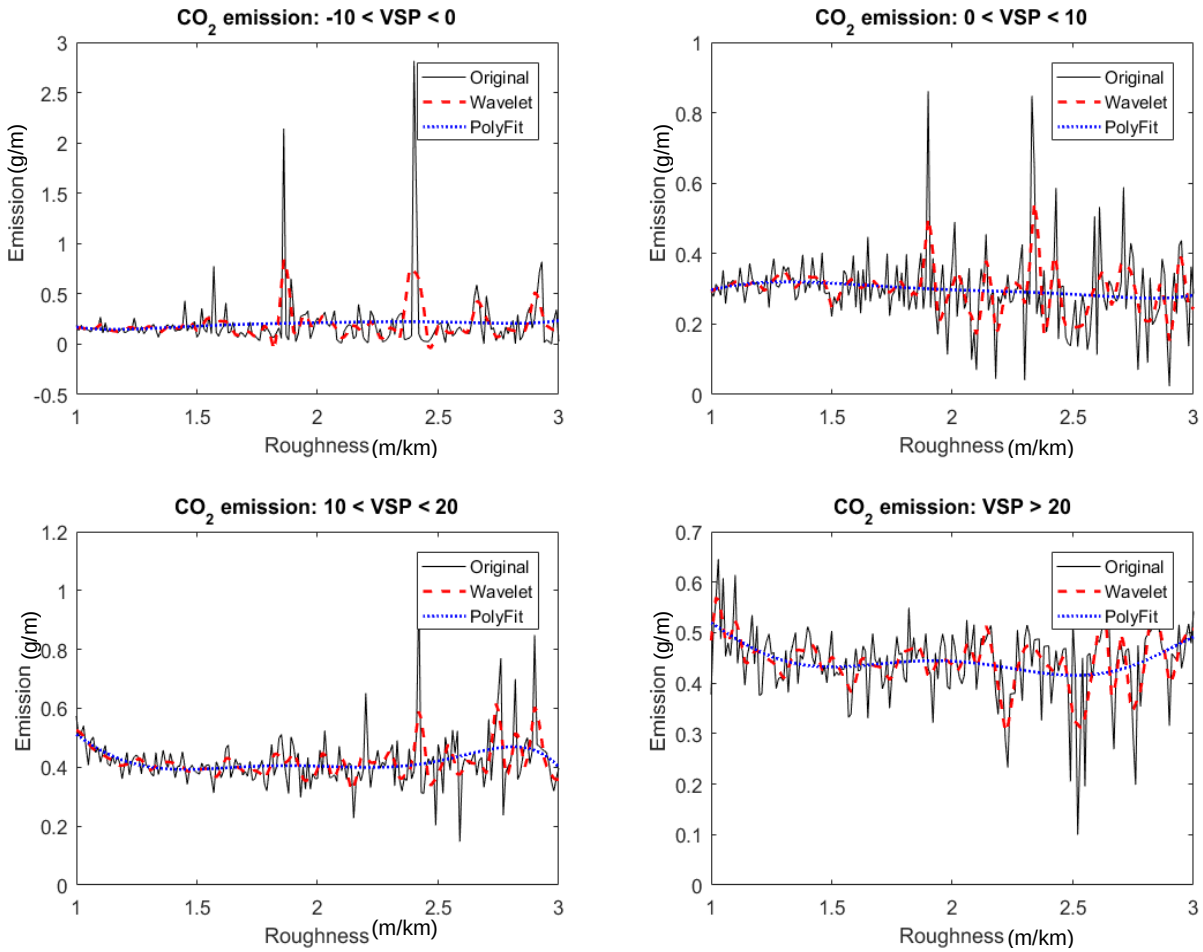
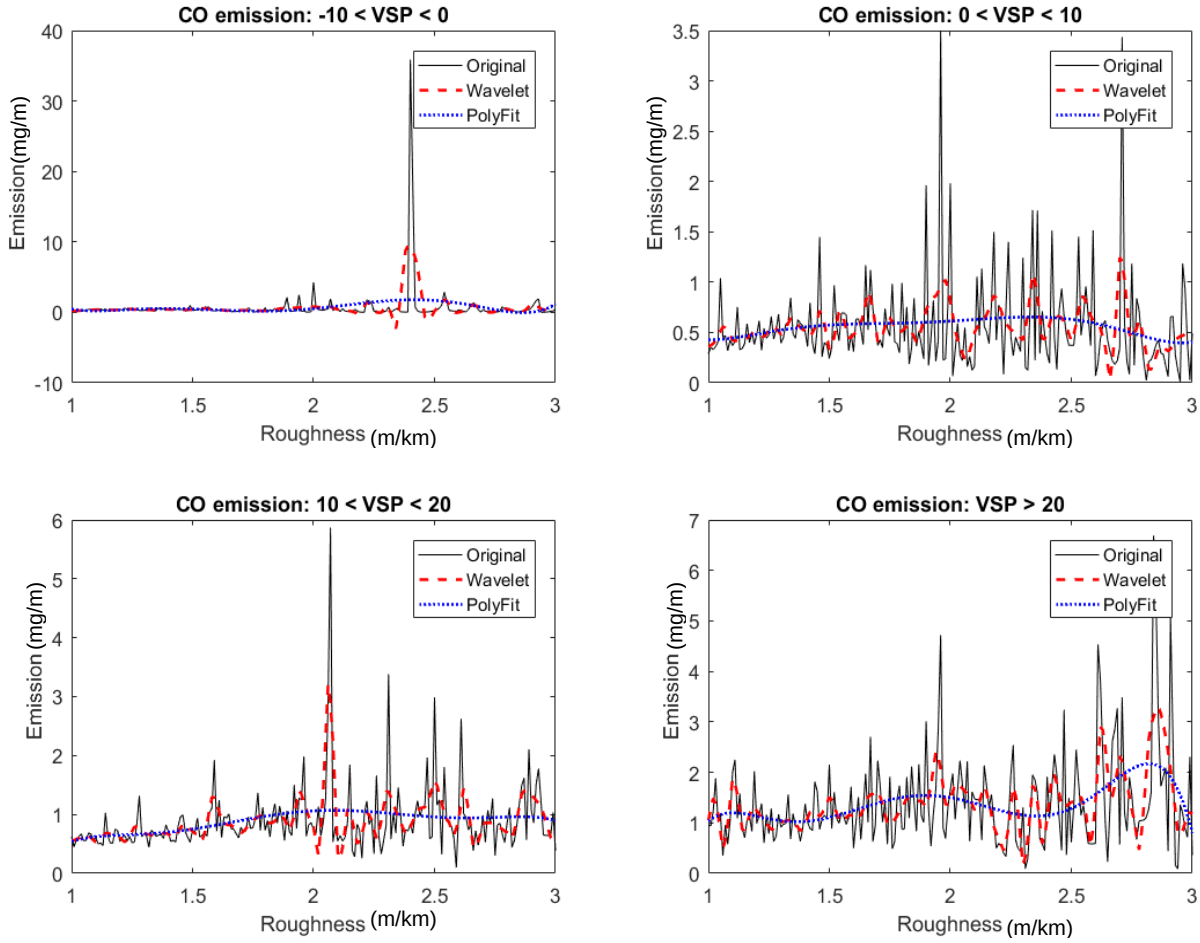



**Fig. 3** Comparison between Wavelet Approximation and Polyfit of $CO_2$ emission for different VSP ranges

Similarly, Fig. 4, 5, 6 and 7 show the comparison among original, wavelet and PolyFit data of CO, HC, $NO_x$ emission and FC correspondingly for the four different VSP ranges. All of them have very sharp peaks for negative VSP than the other VSP ranges. A distinct superiority of wavelet analysis is visible in all the figures in case of approximating the original data over polynomial fitting. Following the analysis of $CO_2$, the other analysis also imply that the polynomial fitting can only follow the general trend of the data, whereas wavelet approximation captures the details of sudden rise and fall observed in PEMS data as well. Therefore, overall analysis qualifies wavelet analysis to be a better candidate in approximating emission vs roughness trends for untested pavements.

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232 **Fig. 4** Comparison between Wavelet Approximation and Polyfit of CO emission for different VSP ranges

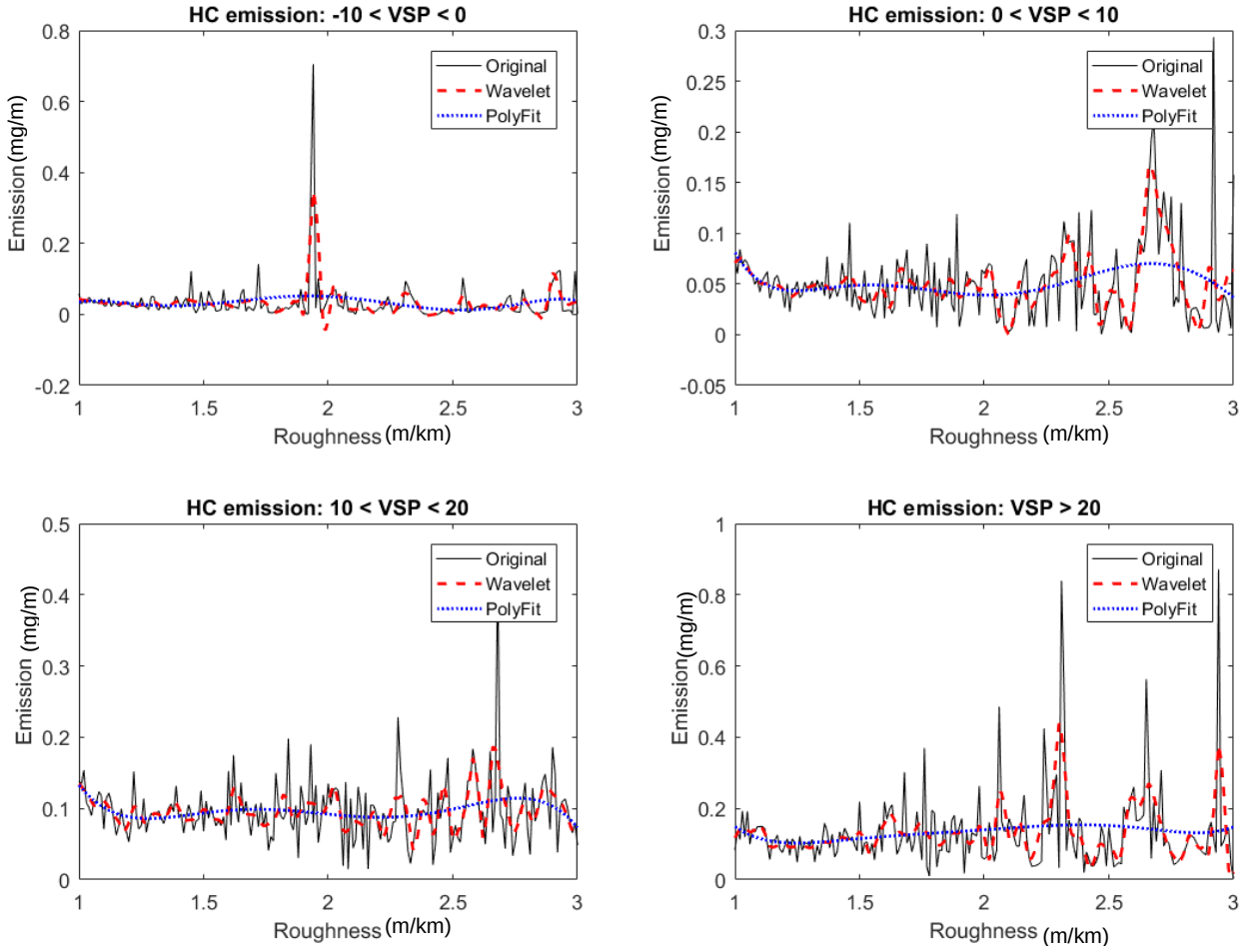


**Fig. 5** Comparison between Wavelet Approximation and Polyfit of HC emission for different VSP ranges

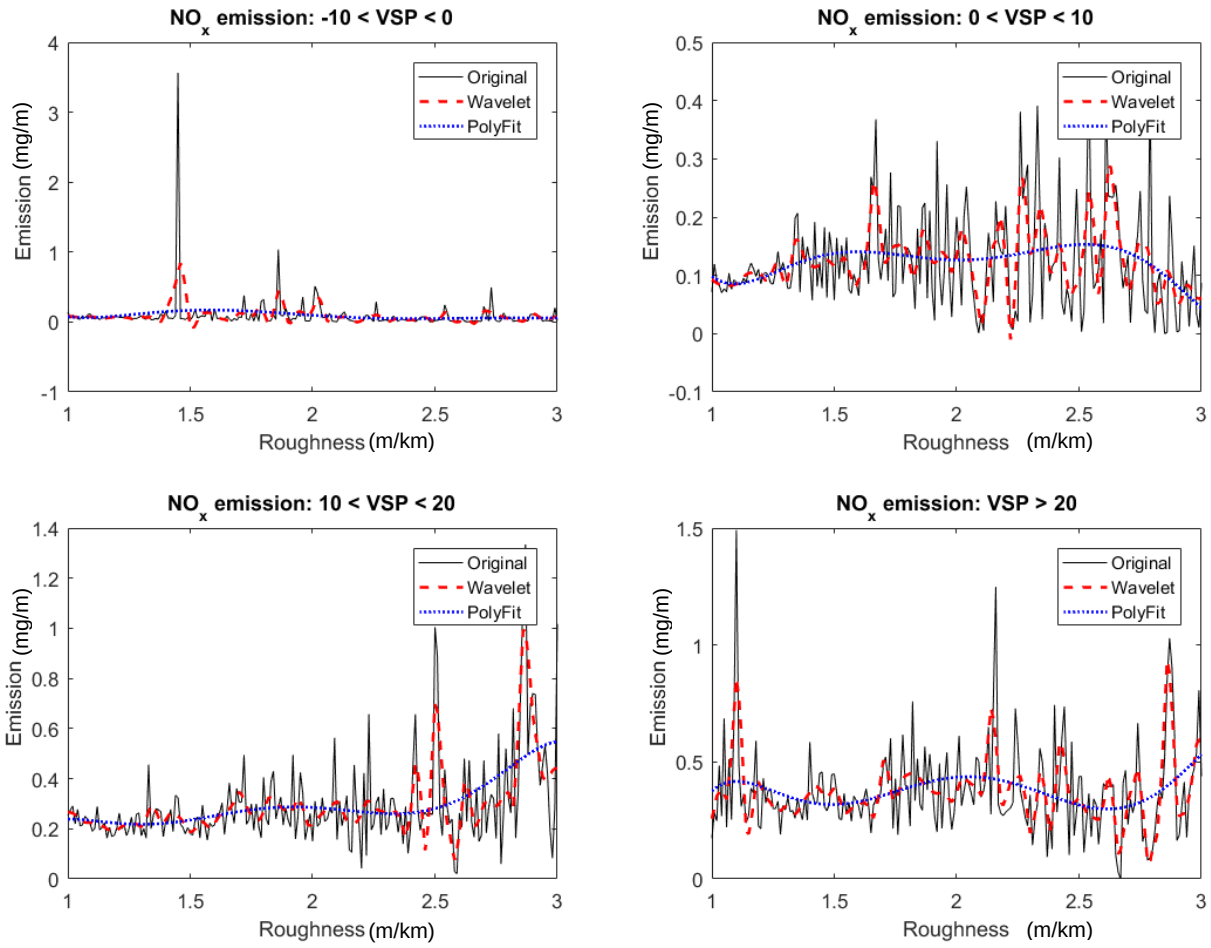


**Fig. 6** Comparison between Wavelet Approximation and Polyfit of $NO_x$ emission for different VSP ranges

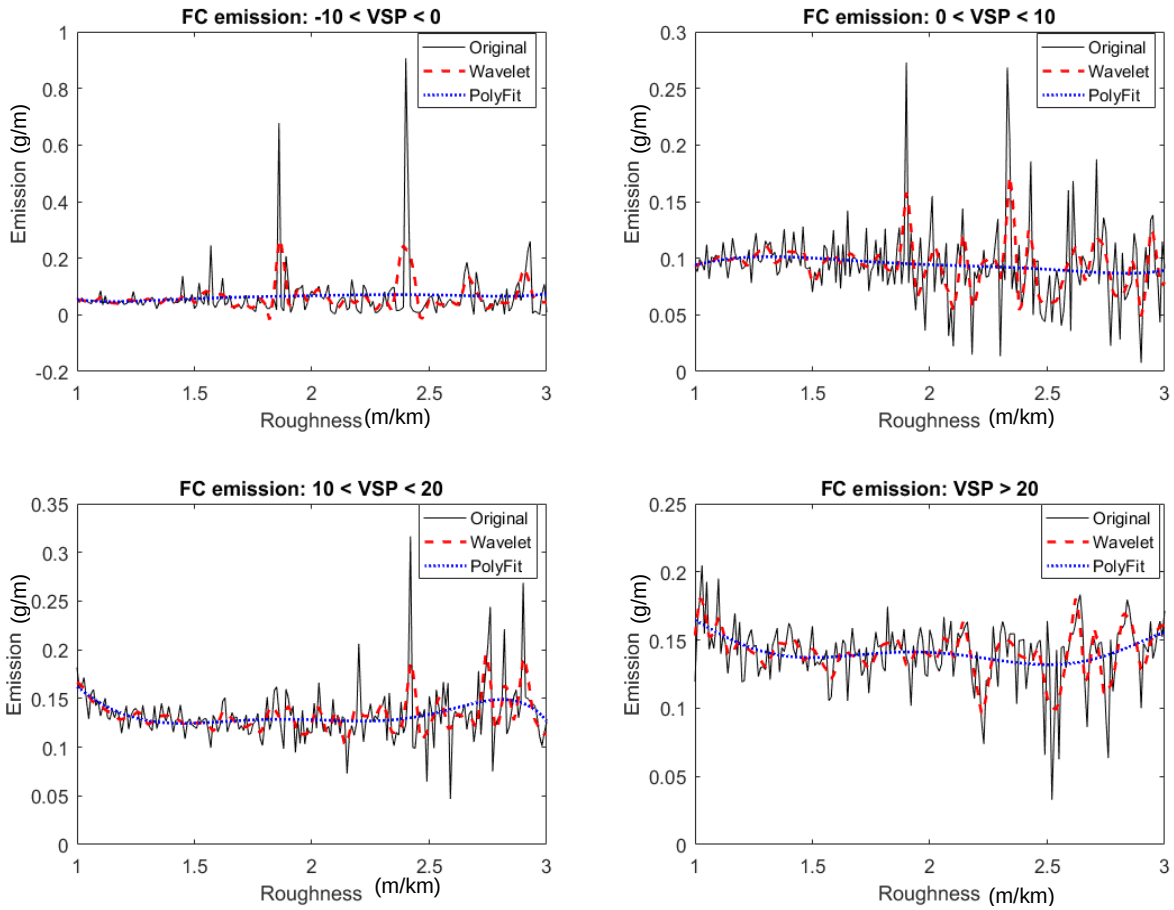


**Fig. 7** Comparison between Wavelet Approximation and Polyfit of fuel consumption for different VSP ranges

A general trend of emissions and fuel consumption can be recognized from above figures. For $CO_2$, CO and HC emissions and also FC are lower in negative VSP, 0< VSP<10 and 10<VSP<20 bins for lower pavement roughness and then the emissions become higher as the roughness increases. Only $NO_x$ shows somewhat different trend than the other emissions having larger emissions at the middle range of roughness within negative VSP range. For the bin where VSP>20, $CO_2$, $NO_x$ and FC are showing initial spike of emissions for lower roughness and increases again for the higher IRI.

### *6.2 Error Measurement for Wavelet Approximations and Polynomial Fitting*

The Root Mean Square Errors, shown in Eq. (6), from Wavelet approximation analysis and Polynomial curve fitting were calculated for each gas and FC and for every VSP range. The Table 1 shows that the RMSE calculated for Wavelet is less than RMSE calculated for Polyfit. Thus, wavelet approximation

249 performs better than the polynomial approximation in all five emissions. However, the root mean square
250 error for both analyses is relatively higher for negative VSP than the positive ones. We believe this is
251 due to the presence of sharp, large-valued emission peaks that were observed in negative VSP regime.
252 Our previous study also indicated large emission vs roughness trend for negative VSP and, thus we can
253 univocally assume that sources of such emissions should be addressed in order to realize more
254 fuel-efficient transportation.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_{observed} - y_{model})^2}{n}} \quad (6)$$

255

256 where, n is the number of data and RMSE = Root Mean Square Error

257 **Table 1** RMSE of Wavelet Approximation and PolyFit

| Emission | VSP range | Polyfit RMSE | Wavelet RMSE |
|---|---|---|---|
| CO | -10<VSP<0 | 2.7883 | 2.4174 |
| | 0<VSP<10 | 0.4506 | 0.4163 |
| | 10<VSP<20 | 0.5535 | 0.4421 |
| | VSP>20 | 0.8739 | 0.7518 |
| $CO_2$ | -10<VSP<0 | 0.2799 | 0.2427 |
| | 0<VSP<10 | 0.1046 | 0.0866 |
| | 10<VSP<20 | 0.084 | 0.0719 |
| | VSP>20 | 0.0677 | 0.0526 |
| HC | -10<VSP<0 | 0.0578 | 0.0419 |
| | 0<VSP<10 | 0.0376 | 0.0287 |
| | 10<VSP<20 | 0.0422 | 0.0368 |
| | VSP>20 | 0.108 | 0.0871 |
| $NO_x$ | -10<VSP<0 | 0.2637 | 0.2380 |
| | 0<VSP<10 | 0.0812 | 0.0682 |

| | | | |
|---|---|---|---|
| | 10<VSP<20 | 0.1592 | 0.1218 |
| | VSP>20 | 0.1821 | 0.1369 |
| **FC** | -10<VSP<0 | 0.0895 | 0.0776 |
| | 0<VSP<10 | 0.0331 | 0.0274 |
| | 10<VSP<20 | 0.0265 | 0.0227 |
| | VSP>20 | 0.0215 | 0.0166 |

## 7 Conclusions

In this paper, the relatively new technique of wavelet transformation and analysis has been employed to analyze the relation of emission and road roughness profile. The application methods and procedures for performing the analysis have been presented in detail which included the use of approximation signal generated from multi-level discrete wavelet transform. Based on the analysis presented in this paper, it can be concluded that wavelet analysis possesses the ability to perform local analysis on PEMS data to identify emission trends more accurately than other common nonlinear analysis. In addition, it has been shown that the analysis can be done for different VSP to understand the emission trend for different vehicular conditions. Thus, 1D DWT can be considered as an effective means of estimating emissions for highway engineers to plan on reduction of vehicular emissions on road.

## Acknowledgments

The authors acknowledge that this research is supported in part by the National Science Foundation (NSF) under grants #1137732, and the U.S. National Tier 1 University Transportation Center (UTC) TranLIVE #DTRT12GUTC17/KLK900-SB-003. The opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the funding agencies. The authors would also like to thank Shah Mohammad Bahauddin for his invaluable discussion and comments on discrete wavelet transformation.

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