Monitoring ride Quality on roads with existing sensors in passenger cars

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Philippe Nitsche

AIT Austrian Institute of Technology

Isabela Mocanu

AIT Austrian Institute of Technology

Leif Sjögren

Swedish National Road and Transport Rese…

MONITORING RIDE QUALITY ON ROADS WITH EXISTING SENSORS IN PASSENGER CARS

Philippe Nitsche, AIT Austrian Institute of Technology, Austria

Carl Van Geem, Belgian Road Research Centre (BRRC), Belgium

Rainer Stütz, AIT Austrian Institute of Technology, Austria

Isabela Mocanu, AIT Austrian Institute of Technology, Austria

Leif Sjögren, Swedish National Road and Transport Research Institute (VTI), Sweden

ABSTRACT

In this paper, a cost-effective method for monitoring and evaluating the ride quality of roads based on probe vehicle data is presented. Running vehicles experience a broad spectrum of vibrations that occur in response to excitation inputs such as the pavement, tires and the engine. In this work, ride quality is expressed in terms of pavement condition including evenness, potholes and other surface irregularities. Data from built-in sensors such as accelerometers and wheel speed sensors are processed by a support vector machine (SVM) and are coupled with local and global positioning using GNSS data to identify sections with poor ride quality. Results are promising and demonstrate that poor ride quality can be accurately localized in a road network. The proposed method enables infrastructure monitoring done by conventional passenger cars, which can be seen as a supplement to prevalent road measurements with cost-intensive mobile devices.

INTRODUCTION

Currently, road administrators collect high-quality road monitoring data that is necessary to make prognosis models and monitor performance of a chosen strategy, thus supporting long-term road management. The data is collected on a regular (e.g. yearly) basis, with dedicated measurement devices. The devices are complex, their operators need to be highly skilled and the execution of measurements is costly. Accordingly, in most cases only the major roads of a network (e.g. motorways) are regularly monitored. A complementary ride quality monitoring technique using a fleet of probe vehicles would not replace the dedicated “high-tech” measurement devices, but can change their role. The information gathered from probe vehicles can steer the use of dedicated devices to the road sections where a significant ride quality problem is identified by the probe vehicles. In this way, the dedicated devices will no longer have to cover the whole road network and can be sent to particular “hot spots”.

This paper presents the outcome of one of the tasks of TRIMM (“Tomorrow’s Road Infrastructure Monitoring & Management”), a research project conducted under the seventh Framework programme of the European Commission. The project deals with different types of inspection techniques for road characteristics, using existing but only recently developed sensor technology, as well as with the integration of these new methods in asset management. The aim of the work described in this paper is to enhance the ability to monitor road functionality, by making use of real-time ride quality monitoring with probe vehicles. The probe vehicles considered in the study are common, commercial passenger cars. The measurements are made during normal drives, as they are done by ordinary drivers. Vehicle dynamics are recorded by sensors that are already included in the vehicles’ equipment, e.g. by extracting data already available on the CAN-bus of the vehicle. This will constitute a crowd sourcing possibility and provide an additional advantage, since data from many cars can be used to increase reliability.

The paper is structured into five sections. The following section gives an overview about state-of-the-art ride quality measurements and common indicators describing it. Subsequently, the research methodology is explained including data collection, reference measurements, post-processing as well as the ride quality estimation method proposed, which is based on analysing vehicle response on different pavement surfaces. In the results section, the estimator output is compared with reference measurements. The paper is concluded with final comments and future research recommendations.

BACKGROUND ON RIDE QUALITY EVALUATION

Ride quality is defined by the perception of a road user's driving experience, which is influenced by numerous factors such as pavement unevenness (e.g. vibration, shock), road alignment, noise in the car, lack of friction and light conditions. Poor ride quality can be related to a range of frequencies, defined in the ISO standard 2361-1 (ISO, 1997). For the comfort of seated persons, the frequencies in the range of 0.5 Hz and 80 Hz are to be considered. However, the ISO standard states that the acceptability of vibrations depends on other parameters as well, such as the trip duration, the passengers' activities (e.g. reading, eating, and writing), acoustic noise, temperature etc. The ISO norm prescribes the use of the weighted root-mean-square acceleration as the basic evaluation of vibration.

This paper considers the unevenness in longitudinal direction of the road surface as the major parameter for poor ride quality. Most studies have found that road evenness, often called roughness, is among the most statistically significant factors associated with driver-perceived ride quality (cf. Shafizadeh et al., 2002). The final report of the COST action 354 (cf. Litzka et al., 2008) contains an overview of the indicators for the evaluation of technical properties of roads in use in 2006-2008 in Europe and beyond – including those for longitudinal evenness.

The longitudinal evenness is evaluated worldwide with different measurement devices and the results can be expressed in numerous indices like the *International Roughness Index* (IRI, cf. Sayers, Gillespie, & Paterson, 1986), the *Notes par Bandes d'Ondes* (NBO, cf. *Mesure de l'uni longitudinal des chaussées routières et aéronautiques*, 2009), the *Evenness Coefficient* (EC, cf. Gorski, 1981) and others (cf. Litzka, Leben, LaTorre, & Weninger-Vycudil, 2008). It can also be evaluated by the *Power Spectral Density* (PSD, cf. CEN, 2006) analysis or with the *Weighted Longitudinal Profile* (WLP, cf. Maurer, Spielhofer, Kempkens, & Ueckermann, 2008; Ueckermann & Steinauer, 2008). These indices are all technical indicators expressing a property of the road surface. Road managers must have a functional "key performance indicator" (KPI) expressing this property in a simple way (on a simple scale without units). The KPI must be measurable in an objective way and must correctly express the ride quality as the user would evaluate it.

A popular indicator, the IRI, is derived from the response of a standard quarter-car model to road profile deviations when driving with a speed of 80 km/h. However, the IRI is most sensitive for certain wavelengths that, in correspondence to body response, can cause discomfort for humans. In 'Introduction to the International Roughness Index' (2007), the author indicates two frequency ranges that influence the IRI and hence cause discomfort: the range between 1 Hz and 2 Hz relates to a car-body bounce and the range between 10 Hz and 12 Hz relates to an axle hop. However, a study reported by Hou, Liang, Ma, & Hua (2009) shows that the IRI is not an optimum indicator for the evaluation of "human body ride comfort". In other words, the IRI is a parameter for vehicle response and not directly for human body response, as already stated by Sayers & Karamihas (1997).

When considering the longitudinal evenness measured by a dedicated measurement device as an input signal, it can be decomposed by Fourier transformation in a combination of waves with various wavelengths. The frequencies of interest correspond to different wavelengths according to the speed at which a vehicle drives over the road, connected by the formula $\lambda = v/f$ where λ is the wavelength (in metres), v the speed (in metres/second) of the vehicle and f the frequency (in Hz). As mentioned before, the PSD and the WLP are two other technical indices for road evenness. The PSD is a spectral quantity proportional to the square of the wavelengths' amplitude represented in the road profile. If the PSD is represented in a graph as the ordinate against the spatial angular frequency as the abscissa, the slope of the "fitting" straight line represents the *waviness* of the road. A correlation between the waviness and the weighted root-mean-square acceleration is reported by Hou et al. (2009), while the authors in the same paper state that they could not find a correlation with the IRI. The WLP is related to the PSD, but applies a treatment of the measured data to a section of a given evaluation length (e.g.

102.4 metres) in four calculation steps: the transformation of the measured profile to the spectral domain and division by a reference spectrum, an octave-band filtering of the referenced spectrum, inverse Fourier transformation and assembling of the octave-band filtered signals and the calculation of the standard deviation and the range of variation of the weighted longitudinal profile (cf. Maurer et al., 2008; Ueckermann & Steinauer, 2008). Therefore, the PSD analysis and the WLP could be more suited for "ride comfort" evaluation, than indicators computed from road profiles considered as a combination of waves with different wavelengths.

METHODOLOGY

As mentioned above, ride quality is related to road evenness. The proposed methodology for estimating evenness is based on the dynamic response of a passenger car travelling on a road. Figure 1 depicts the methodology, including the collection and processing of probe vehicle data (upper part), as well as the preparation of reference data (lower part).

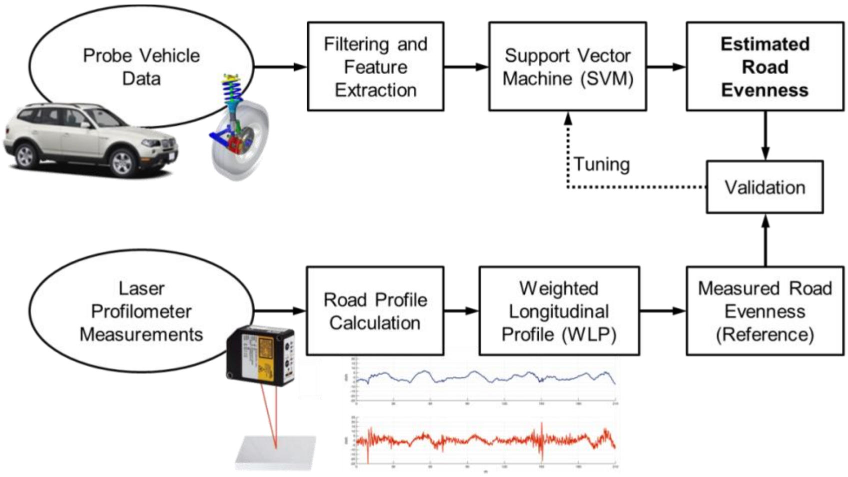

Figure 1: Methodology

The overall goal of this research is to estimate evenness based on probe data without conducting high tech measurements with dedicated profilometer devices. To this end, a support vector machine is applied to classify vehicle dynamics data from probe vehicles into four different evenness classes. The WLP is used as reference indicator for evaluating longitudinal pavement evenness. The following subsections explain how vehicle and reference data were collected and further processed.

Reference data

The reference data for road evenness were collected with an inertial profiler. Inertial profilers are dedicated devices for determining the longitudinal profile of a road. The system consists of two components: a laser triangulation sensor with a vertical resolution of 30 μm and an accelerometer with a resolution of 540 μg on a rigid platform. The measurements are done in the right wheel track. Both sensors are sampled with a frequency of 1 kHz, which leads to a horizontal resolution of 1.6 cm when measuring with a constant speed of 60 km/h. The operating principle of the inertial profiler is as follows: the vertical acceleration is doubly integrated over time and provides the inertial position of the measurement device in motion. The displacement measured by the laser sensor is subtracted from the inertial position. The result is the true profile of the road in the time domain. The signal is transferred to the spatial domain and band-pass filtered to a wavelength range of 0.5 to 50 m according to the definition of unevenness in EN 13036-5.

In this work, ride quality is defined by road pavement evenness, expressed by the WLP. This evaluation method has been chosen due to the following reasons: First, it is capable of distinguishing between three different phenomena of evenness (see Figure 2), namely 1) general roughness, 2) (pseudo-) periodical roughness and 3) singular irregularities. This allows considering a broader spectrum of pavement condition than by just using one indicator such as the IRI. Secondly, the WLP is independent of vibration behaviour and speed.

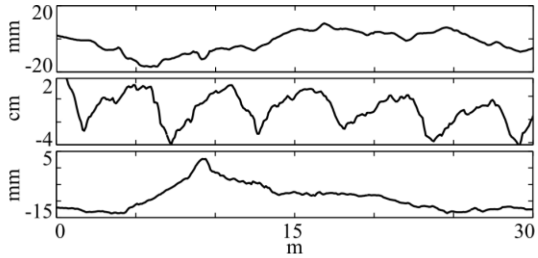

Figure 2: Examples for three types of roughness phenomena: general (top), periodic (middle) and single irregularities (bottom)

In order to obtain the WLP, the following calculations must be performed. The true road profile $z(x_i)$ measured with the profiler is segmented into sections with a length of 50 metres with a sampling distance of 0.1 metres. In order to obtain a sample size of 2^n for a Fourier transformation, the sections are enhanced to 2048 profile points x with overlapping segments before and after. As a first step, the segmented profile must be transformed into the frequency domain. As proposed by Ueckermann & Steinauer (2008), the transformed profile $\underline{z}(x_i)$ is then filtered by a fourth order Butterworth high-pass filter H with a cut-off wavelength L_c of 50 m and maximum wavelength L_s of 204.8 metres, which can be written as $\underline{Z}(k) = \underline{z}(k) \cdot H(k)$. The weighted spectrum is calculated as $\underline{Z}_w(k) = \underline{Z}(k) \cdot W(k)$, where the weighting function is given by

$$W(k) = \begin{cases} \widetilde{W}(k), & 0 \leq k < 1025 \\ \widetilde{W}(2048 - k), & 1025 \leq k < 2048 \end{cases}$$

and

$$\widetilde{W}(j) = \sqrt{\frac{\left(j \frac{L_c}{L_s}\right)^{\alpha - 1}}{2^{\frac{\alpha-1}{2}} - 2^{-\frac{\alpha-1}{2}}}}$$

The purpose of the weighting function is to amplify single as well as (pseudo-)periodical irregularities in the profile. The road's waviness α is a measure of the amplitude ratio between short and long wavelengths of a profile and typically has values between 2.0 and 2.8, depending on road network characteristics. By modifying α, one can give special emphasis on short or long wavelengths. Basically, the higher the proportion of short-wave irregularities on a pavement, the higher the waviness should be chosen. Since the test tracks used for this work have a high proportion of concrete pavements and therefore mostly short-wave irregularities, a value of 2.6 was used.

The weighted spectrum $\underline{Z}_w$ is then separated into ten octaves, where each of these octave bands is separately re-transformed into the space domain. The overlaps of each single profile are cut off to obtain the original section length of 50 m. Consequently, there are ten weighted profiles $z_{w,j}$ with $1 \leq j \leq 10$, whose weighted sum results in

$$WLP = \sum_{j=1}^{N=10} \frac{\sigma_{w,j}}{\sigma_{w,all}} \cdot z_{w,j}$$

where σ_w is the standard deviation. From the weighted profile, two characteristic values are calculated: the range Δ_{WLP} and standard deviation σ_{WLP} of the WLP. These can be compared to the respective threshold values given by the national road maintenance guidelines. In this paper, both values are considered as the target variables for the estimator. A difficulty in estimating road evenness is that the data contains outliers, which should not be discarded but rather might indicate dangerous sections along a road, e.g. where the pavement is damaged. Such single irregularities (e.g. potholes) are indicated by a higher Δ_{WLP}, while roughness showing periodical patterns produces a higher σ_{WLP}.

In this work, a ride quality rating based on previous studies is used. For example, Shafizadeh et al. (2002) compared drivers' perception of road roughness (from 1 to 5, i.e. very smooth to very rough) to IRI measurements. Their results indicated that driver rankings increased as the IRI increased, although factors associated with the roadway, the test vehicle and the individual must also be taken into account. Another study compared the IRI with the WLP for thirty different test tracks and published an evenness class rating based on certain thresholds for the IRI, for Δ_{WLP} and σ_{WLP} (cf. Spielhofer, Brožek, Maurer, Fruhmann, & Reinalter, 2008, p. 211). This 5-class approach is based on the Austrian regulations published by FSV (2006) and was slightly adapted for this work by optimizing the thresholds and reducing the class number to four. The findings of Shafizadeh et al. (2002) on roughness perceived as acceptable as well as the distribution of the proposed WLP classes in the reference data were taken into account. Accordingly, four classes with thresholds as given in Table 1 were derived, where "1" refers to very good ride quality (due to smooth roads) and "4" to very bad ride quality (due to rough roads).

Table 1: Ride quality classes and thresholds

Indicator/class	1	2	3	4
IRI [m/km]	$\mathbf{0 \leq IRI < 1}$	$\mathbf{1.0 \leq IRI < 3}$	$\mathbf{3 \leq IRI < 4.5}$	$\mathbf{IRI \geq 4.5}$
Δ_{WLP} [mm]	$0 \leq \Delta_{WLP} < 25.2$	$25.2 \leq \Delta_{WLP} < 42.5$	$42.5 \leq \Delta_{WLP} < 75$	$\Delta_{WLP} \geq 75$
σ_{WLP} [mm]	$0 \leq \sigma_{WLP} < 4.2$	$4.2 \leq \sigma_{WLP} < 7.2$	$7.2 \leq \sigma_{WLP} < 12.5$	$\sigma_{WLP} \geq 12.5$

Collection of data

This section describes the collection of probe vehicle data used to train the SVM. All measurements were performed with a probe vehicle that is capable to measure vehicle dynamics as well as reference data, i.e. longitudinal evenness. The vehicle is equipped with multiple high-performance measurement systems connected to an independent power supply, in order to ensure stable and optimum functionality (see Figure 3). The sensors are able to collect data regarding high precision positioning via GPS coupled with an inertial measurement unit (IMU), longitudinal evenness of a pavement (measured with a laser sensor), driving dynamics, road geometry and others. The measurement systems are connected to a data acquisition system, which allows storing and downloading data at any moment.

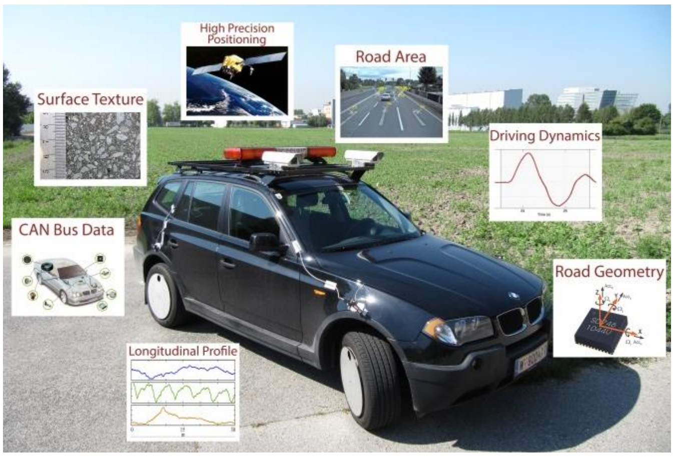

Figure 3: Probe vehicle and collected data

The collection of vehicle dynamics and reference (laser) data was performed simultaneously. Common vehicles are nowadays equipped with multiple sensors that assist in the operation and performance of a vehicle. The sensors are all connected to a standard communication bus called Controller Area Network (CAN). Therefore, vehicle dynamics data was gathered by connecting the CAN bus to the vehicle's acquisition system. In addition, a three-axis accelerometer mounted near the middle-console delivered vehicle motion data, especially vertical acceleration that are not available in the CAN bus messages. In summary, the following sensor data were recorded for this work:

- Longitudinal, lateral and vertical acceleration, given in m/s²

- Steering wheel angle, given in degrees
- Front and rear wheel speeds, given in km/h
- Brake/clutch state, given by 0/1
- Engine rotation speed given in number of revolutions per minute (rpm)
- GPS data: time, position, speed, satellite number, dilution of precision, heading
- Longitudinal road profile: reference data given in mm

From the longitudinal profile data, the reference WLP data was computed. It is important to note that apart from the sophisticated on-board data acquisition system, this probe vehicle still shows “normal” vehicle dynamics. Although the method in this work is trained on this particular vehicle, it can be expected that other vehicles of a similar vehicle class produce comparable data.

A support vector machine—which is used for estimating evenness in this work—is a machine learning method, i.e. it requires training data and corresponding target values as a teaching input. Therefore, a comprehensive measurement campaign with the probe vehicle was conducted in the area of Vienna, Austria. In total, approximately 88 km of road were measured, from which 59 km were on the motorways and 29 km on urban roads. It was ensured that these data included very rough to very smooth pavements to get a representative sample. For urban roads, the measurement speed was around 50 km/h, for motorways around 80 km/h.

Post-processing and feature extraction

While the profilometer recorded with a sample distance of 0.1 metres, probe vehicle data was processed with a fixed sample distance of 0.05 metres. Since wheel speed data is mainly interesting due to short-term variations when running over a surface irregularity, the respective vehicle speed was reduced from the wheel speed signals for each sample. This resulted in wheel speeds moving around zero.

Road evenness is defined by wavelengths between 0.5 and 50 metres. Greater wavelengths belong to road alignment and can be neglected for evenness estimation. Wavelengths below 0.5 metres define a road property called texture. Frequency analyses in the scope of this work showed that the longitudinal and vertical acceleration signals as well as the wheel speed signals have a similar spectral behaviour like evenness. A band-pass filter (Butterworth of third order) is therefore applied to these data. In order to enable location-based ride quality monitoring, the filtered data were segmented into road stretches of a certain length. This allowed calculating a set of features from in-vehicle sensor data for each segment and comparing it to the ride quality indicator computed from reference measurements, further denoted as target data. In other words, collected data is divided into moving windows. Each window consists of 2000 samples in succession, comprising a length of 100 metres with a step length of 20 metres between two subsequent segments. The segments overlap to gain more training data for the estimator.

For each segment, 81 features are computed from the measurement data given in the previous paper section. This includes arithmetic mean, standard deviation, range and arithmetic mean of the Short Time Energy (STE) for each of these variables. The latter one is primarily used in the field speech and voice recognition for distinguishing between voiced and unvoiced parts of a speech signal (Rabiner & Schafer, 2007). Furthermore, power spectral densities for ten equally sized frequency bands between 0.1 Hz to 1 Hz are computed to take frequency behaviour into account. All features were centred to mean 0 and scaled to standard deviation 1.

Some segments may include special driving manoeuvres such as strong acceleration, gear changes or steering movements, all of which influence vehicle dynamics. Hence, data in these segments does not solely reflect ride quality and may lead to erroneous evaluation results. To eliminate this influence, only those segments in which the driver does not push the brake or accelerator pedal, and the steering wheel angle does not exceed +/- 20 degrees, are presented as input data.

Estimation of evenness

The estimation of evenness is based on an inverse modelling approach, i.e. the road evenness is calculated from the vehicle dynamic response, which usually causes ride discomfort due to vibrations. This principle is depicted in Figure 4 and further explained in this section.

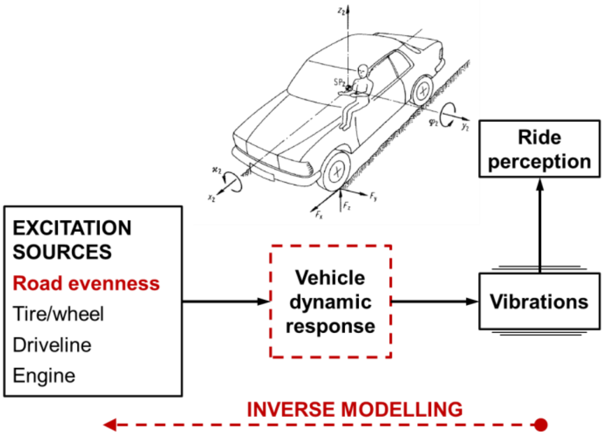

Figure 4: Principle of inverse modelling (based on Gillespie, 1992)

Support vector machines were originally developed for two-class classification problems. Vapnik, Golowich, & Smola (1997) proposed a SVM for regression problems, which is called support vector regression (SVR). SVR has the design of a feed-forward neural network and can be considered as an extension of the perceptron. These models have demonstrated highly competitive performance in numerous real-world applications, which have established support vector machines as one of the state of the art tools for machine learning (Wang, 2005). They can be used for various function approximation, regression and (time-series) prediction tasks. Recently, the effectiveness of several nonlinear regression models in estimating the key indices of the WLP have been compared (Nitsche, Stütz, Kammer, & Maurer, 2012). These models include multilayer perceptrons, random forests and support vector machines, the latter of which turned out to be the most reliable.

The basic idea of the ε-SVR algorithm is that data points from the p-dimensional initial space are mapped by a (nonlinear) transformation function Φ to a high-dimensional hidden feature space $\mathcal{F}$. In this feature space, a linear model is constructed, which corresponds to a nonlinear regression in the low dimensional input space $f(x) = w^T\Phi(x) + b$, where $w \in \mathcal{F}$ denotes a weight vector and $b \in \mathbb{R}$ is the bias term. The aim is to find a function $f(x)$ that is both as smooth as possible and deviates maximally from the targets y_i by ε, i.e. an ideal estimation is achieved when all absolute residuals are within ε (the so-called ε -insensitive region). The SVR minimizes the squared norm of the weight vector w, while it linearly penalizes deviations greater than ε using a piecewise linear loss function. To allow for model errors greater than ε, non-negative slack-variables $\xi_{+,i}$ and $\xi_{-,i}$ are introduced, otherwise this problem could be infeasible. This results in the quadratic optimization problem with cost parameter $C > 0$

$$\min_{w,b,\xi_{+,i},\xi_{-,i}} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_{+,i} + \xi_{-,i}),$$

subject to the linear constraints

$$y_i - w^T h(x_i) - b \leq \varepsilon + \xi_{+,i},$$

$$w^T h(x_i) + b - y_i \leq \varepsilon + \xi_{-,i},$$

$$\xi_{+,i} \geq 0, \xi_{-,i} \geq 0.$$

From these equations, the corresponding dual problem can be derived by using the Karush-Kuhn-Tucker conditions, which is more convenient to solve by quadratic programming techniques than the primal problem. Since the SVR is expressed by a convex quadratic optimization problem, the solution is globally optimal. This is in contrast to neural networks, where the back-propagation algorithm usually converges only to locally optimal solutions. The mapped input vector appears only in the form of scalar products in the dual formulation. To avoid the evaluation in the high-dimensional feature space, the scalar products are replaced by a chosen kernel function $K(x_i, x_j) = h(x_i)^T h(x_j)$. This is known as the so-called *kernel trick.* There are many possible kernels, but all of them should fulfill Mercer's condition to be an admissible kernel (Abe, 2005). A popular choice is the (Gaussian) radial basis function kernel, or RBF-kernel, which is defined by

$$K(x_i, x_j) = \exp\left(-\gamma \|x_i - x_j\|^2\right),$$

with an additional hyperparameter $\gamma > 0$. The RBF-kernel implicitly maps every point of the input space to an infinite dimensional space.

The cost parameter C, along with the kernel hyperparameter γ, constitute the main tuning parameters of the SVR-model. The cost parameter C determines the trade-off between the training error and model complexity. When the cost parameter is large, the model becomes very flexible and it is likely to overfit the data. Since there is a relationship between the funnel size ε and the cost parameter C, it is not necessary to perform extra tuning for the size of the funnel. This approach is also suggested by Kuhn & Johnson (2013). All computations were performed in the R environment for statistical computing (R Core team, 2014) using the add-on package *caret* (Classification and Regression Training; cf. Wing et al., 2014) for tuning and feature selection. The model fitting was conducted using the SVM implementation in the *kernlab* package (Karatzoglou, Smola, Hornik, & Zeileis, 2004), for which the *caret* package provides appropriate wrapper functions.

Traditional methods in machine learning do not consider correlation between the samples in the training set. Therefore, standard cross-validation procedures with random selection are not appropriate in this study, since the features and target variables exhibit (strong) autocorrelation. It has been observed that this will vastly overfit the data. However, the *caret* package allows for cross-validation via different types of moving windows to resample times series data. The final model parameters were chosen after a cross-validated grid search according to Table 2.

Table 2: SVM tuning parameters

Road Type	Funnel size ε	Cost parameter C	Kernel parameter γ
Motorways	0.1	150	1e-03
	0.1	150	1e-03
Urban Roads	0.1	50	1e-04
	0.1	5	1e-03

RESULTS

In the given validation data set, two road types are considered, namely urban roads and motorways. Since their WLP significantly differ, i.e. urban roads are generally rougher than motorways, these road types were evaluated separately. In total, 1007 urban road segments were used for training, while 461 segments were taken for validating the trained SVM with unknown data. For motorways, 2687 segments were used for training and 261 segments for validation. To show the validation performance of the trained SVM, the following indicators were computed for the predicted and measured Δ_{WLP} and σ_{WLP}, respectively: Correlation coefficient ρ, L1 (least absolute deviations) and L2 error (least squares) and overall accuracy of classification into the four classes given in Table 1. The performance results are listed in Table 3.

Table 3: SVR performance indicators for the urban road validation set

Road Type	Target	ρ	L1 error [mm]	L2 error [mm]
Motorways	Δ_{WLP}	0.879	6.556	100.414
	σ_{WLP}	0.931	0.487	0.7132
Urban roads	Δ_{WLP}	0.902	16.402	25.230
	σ_{WLP}	0.973	1.492	2.012

The SVR shows generally good performance with a ρ between 0.879 and 0.973. σ_{WLP}, i.e. periodical evenness phenomena are more accurately estimated than evenness expressed by Δ_{WLP}. This is true for both road types. The L1 error for the range of the WLP is very low with 6.556 mm and 16.402 mm for motorways and urban roads, respectively. It must be noted that Δ_{WLP} is generally higher for urban roads then for motorways, and so is the error value.

Figure 5 depicts the SVR results for approximately 5 km of different motorway stretches that were used for validation, by comparing the measured to the predicted WLP target variables. It can be seen that the characteristics of the target variables are captured by the SVR. High peaks indicating single irregularities are detected, although not reproduced exactly. It is important to note that the signification drop of evenness around road segment number 160 is accurately predicted.

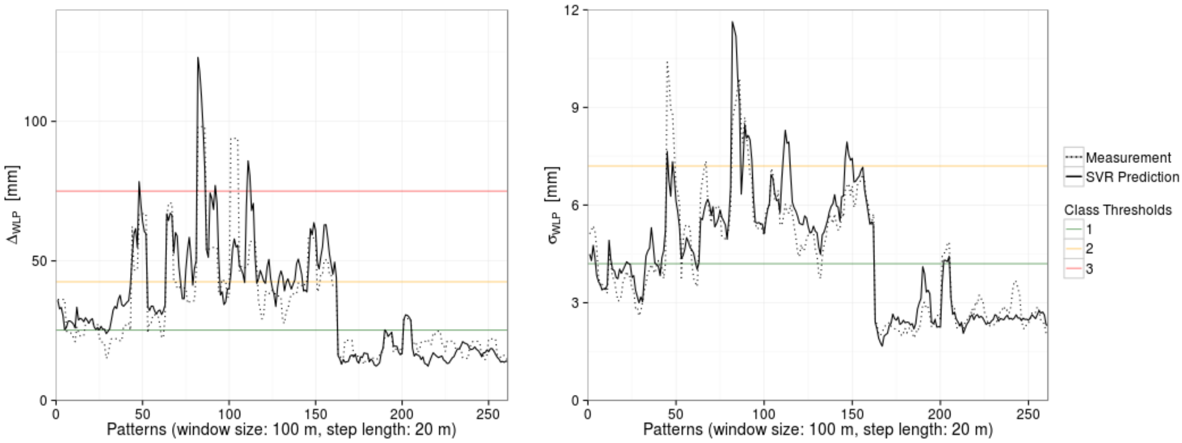

Figure 5: Estimation of Δ_{WLP} (left) and σ_{WLP} (right) for the motorway validation set

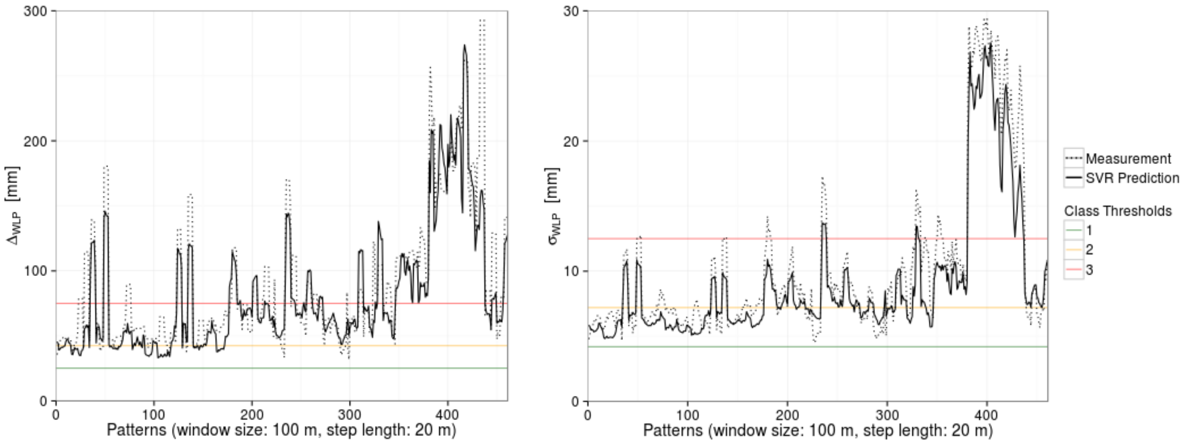

Figure 6: Estimation of Δ_{WLP} (left) and σ_{WLP} (right) for the urban road validation set

For urban roads, the WLP has significantly higher values than for motorways. Accordingly, the validation set shown in Figure 6 exceeds the class 4 threshold (red horizontal line, i.e. very bad ride quality) much more often. In contrast, none of the validation road segments falls into class 1 (indicated by the green line, i.e. very good ride quality). Similar to the motorway validation set, single irregularities and high peaks can be detected, but seem to be underestimated by the SVR. However, general changes of evenness can be predicted reliably.

Confusion matrices were produced to present the results of classification, whereas each row of the matrix represents the instances in the predicted class, while each column represents the instances in the reference class. All correct predictions are located in the diagonal of the table. Table 4 depicts the classification results for the motorway validation set. It can be seen that the model performs better on classifying σ_{WLP} with an accuracy of 85.8 percent. This is due to the fact that Δ_{WLP} includes very sharp peaks and is much less smooth in contrast to the σ_{WLP}. In other words, on the motorways, periodic unevenness can be more accurately classified than single irregularities. Most misclassifications can be observed between Class 2 and Class 3.

Table 4: Confusion matrices for the motorway validation set

Δ_{WLP}		Reference Class			
		1	**2**	**3**	**4**
Predicted Class	**1**	96	1	0	0
	2	26	46	6	0
	3	0	31	41	5
	4	0	0	4	5
Accuracy: 72.0%					

σ_{WLP}		Reference Class			
		1	**2**	**3**	**4**
Predicted Class	**1**	118	3	0	0
	2	18	95	5	0
	3	0	11	11	0
	4	0	0	0	0
Accuracy: 85.8%					

Table 5: Confusion matrices for the urban road validation set

Δ_{WLP}		Reference Class			
		1	**2**	**3**	**4**
Predicted Class	**1**	0	0	0	0
	2	0	11	61	5
	3	0	21	145	46
	4	0	0	11	161
Accuracy: 68.8%					

σ_{WLP}		Reference Class			
		1	**2**	**3**	**4**
Predicted Class	**1**	0	0	0	0
	2	0	172	47	0
	3	0	16	141	22
	4	0	0	0	63
Accuracy: 81.6%					

In Table 5, a similar conclusion can be drawn, as the classification of σ_{WLP} shows superior results with an accuracy of 81.6%. The relatively low accuracy of 68.8% for Δ_{WLP} can be explained by the class thresholds and misclassifications between class 2 and 3. For the given data validation set, the class threshold lie within the range of underestimated Δ_{WLP} (see yellow horizontal line in Figure 5 and Figure 6. Other evenness classes may results in superior classification accuracy.

In summary, when taking the two WLP target variables as different indicators for ride quality, it can be observed that road stretches with periodical to general evenness can be better identified than roads with mainly single irregularities (e.g. potholes). Although potholes would be detected by the estimator with a high probability, the estimated WLP value might differ from the actual value.

CONCLUSIONS

This paper introduced a novel approach for monitoring ride quality of a road by using probe vehicles. To this end, road evenness, or more precisely the weighted longitudinal profile (WLP) was used as ride quality indicator. A method for estimating the WLP based on processing vehicle response from a running passenger car was proposed. A support vector machine (SVM) was trained with vehicle dynamics data collected on road sections of different types and evenness characteristics. Simultaneously, evenness was measured by a profilometer and transformed to the WLP. By doing so, the SVM results could be evaluated with reference data.

The results show that poor ride quality can be accurately detected, although some erroneous classifications were observed at roads with medium evenness. However, the estimator was found to be accurate for very rough and very smooth road sections. It can be concluded that ride quality of roads can be precisely evaluated by using a probe vehicle approach. Thus, the proposed method enables road network monitoring done by conventional passenger cars, which can be seen as a supplement to prevalent road measurements with cost-intensive mobile devices. The added information can be used to provide a performance index for high level asset management, used not for the preparation of a tender for particular road works on a particular road section, but rather for strategic decision making or support on planning of a global policy.

However, there are some limitations that are worth to note. For example, CAN bus data are not always available due to restrictions from the car manufacturers. Without a cooperation with the manufacturers, external on-board devices or smartphones may be a promising alternative, although the amount of data is limited. Furthermore, at the moment, the presented method is optimized for sports utility vehicles (SUVs). Future work will include the collection and processing of data from different probe vehicles as well as recursive feature selection to reduce the high-dimensionality in the probe data.

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AUTHOR BIOGRAPHIES

Philippe Nitsche, born in 1982 in Vienna, Austria, received his MSc. at the University of Applied Sciences Technikum Vienna with a thesis about pavement monitoring with sensors in passenger cars. While working as a researcher at the Austrian Road Safety Board (KFV) for two years, he gained expertise in road crash analysis and prevention. Since 2008, he has been employed as a scientist at the Austrian Institute of Technology, with focus on researching the interaction between vehicles, infrastructure and road users. Within national and international research projects, he published numerous scientific papers in journals and conference proceedings. In behalf of AIT, his Austrian patent on pavement monitoring based on machine learning was granted in 2012. Since 2013, he is an active member of the European iMobility working group “Probe Data” in Brussels.

Carl Van Geem, born in 1968 in Schoten, Belgium, received his Doctor’s degree in technical sciences at the Johannes Kepler University in Linz, Austria. Since 2004, he has been working as a researcher at the Belgium Road Research Centre (BRRC), in the division addressing Road Maintenance Management. The division is able to perform NDT monitoring of roads. He is currently involved in several European research projects on asset management and safety and participated in a project funded by the Flemish Institute for Mobility (VIM), concerning a feasibility study of new technology for pavement management including sensors on board of a fleet of probe vehicles.

Rainer Stütz, born in 1978, studied Applied Mathematics (Mathematical Computer Science) at the University of Linz. Afterwards he worked as an research assistant at the Johann Radon Institute for Computational and Applied Mathematics (RICAM/Austrian Academy of Sciences) in Linz. Since 2005 he holds a research position at the Austrian Institute of Technology (Transportation Infrastructure Technologies). His work focuses on statistical data analysis, data visualization, statistical and mathematical modelling and machine learning.

Isabela Mocanu was born in 1988 in Bacau, Romania. She studied Electronics in Transport and received her Engineering Diploma at the Polytechnic University of Bucharest, Romania and went on to receive her Master Degree at the University of Applied Sciences Vienna, Austria with a thesis on driver behaviour adaptation to electric vehicles. Isabela Mocanu has been working as a scientist at AIT since 2013. Her research interests are cooperative systems, road infrastructure analysis, evaluation of driver perception and behaviour and Intelligent Transportation Systems. She has experience from being project participant in multiple national and European projects.

Leif Sjögren, born in 1953, has been employed at VTI since 1980. Since 1990, he is senior Researcher at VTI and from 1998 responsible for VTI’s field of competence road condition assessment, measurement and analysis. In the years 1992-1997, he was head of the resource group road surface testing development. In the years 2000-2001, he was acting as research director of the unit Measurement and Technology. He has been published numerous scientific papers and coordinated four large-scale European research projects.