Surface Mounted Vehicle Property Sensing for Cooperative Vehicle Infrastructure Systems

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SURFACE MOUNTED VEHICLE PROPERTY SENSING FOR COOPERATIVE VEHICLE INFRASTRUCTURE SYSTEMS

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ABSTRACT

This paper presents first results for vehicle detection and vehicle property estimation based on the assessment of traffic induced vibrations in the road surface. A surface mounted 3D accelerometer device is used to register the vibrations in the surface. Acquired data from experiments on roads are used to design methods that are able to detect vehicle passages, estimate the number of axles of a vehicle and also deduce the wheel-base for passenger cars. Evaluation of the methods indicate that the accelerometer based approach is feasible and should be further developed in order to deduce vehicle properties like vehicle speed and distance to sensing device from one device. Moreover, results for the vehicle detection on real-life traffic data from the E4 in northern Sweden are summarized.

KEYWORDS

Road surface, accelerometer, vehicle detection, traffic induced, vibrations, surface mounted, sensor node

INTRODUCTION

Fatality in road traffic is the dominating cause for non-natural human death in our societies, [2]. These accidents are the main cause of death in the under 45 age group and here cause more deaths than heart disease or cancer. The annual cost to society for all traffic accidents is estimated to exceed 160 billion Euro a year, which corresponds to 2% of EU GNP, [2]. Adding cost for general traffic problems, *i.e.* traffic jams, yields a cost to society of 3% of the EU GNP. There are many ways to address this problem and currently, there are efforts to make the infrastructure and vehicles more intelligent and in the future more integrated. The integration is achieved by sharing information between different sources and by cooperating directly to reduce negative traffic effects.

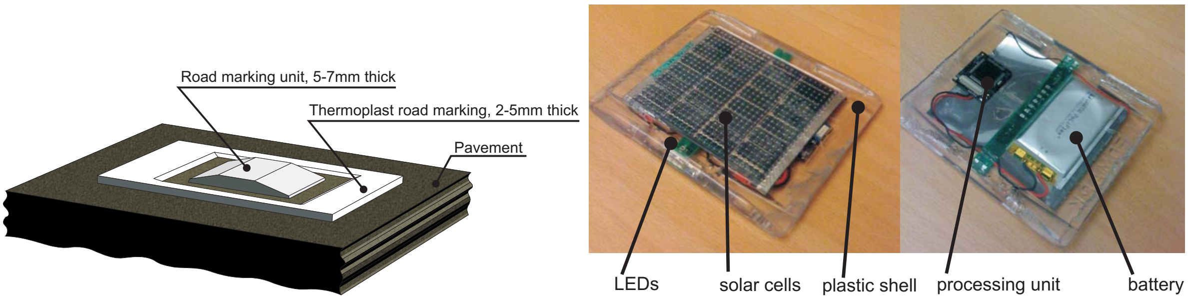

Figure 1 – From left to right: Schematics of a road marking unit and real-life pictures of a road marking unit with integrated electronics (bottom).

One approach is to make the road surface intelligent and equip it with with self-sustained wireless sensor nodes that jointly measure, estimate, take decisions and communicate with drivers, vehicles and other infrastructure elements. The approach taken in this work is to integrate the sensor nodes into the road markings, hereafter denoted road marking units (RMU), see Fig. 1.

Most traffic efficiency and safety functions depend heavily on the assessment of the current vehicular states and traffic dynamics. Meanwhile, the dynamics of a traffic scenario depends on relative contiguities like distances, relative speeds and accelerations. The relativeness is usually between vehicles and/or infrastructural boundaries. Effective solutions to the above mentioned targets hence require information well beyond the local neighbourhood of each vehicle. Again, this urges solutions that involve infrastructure. An example of an infrastructure based application is the overtaking assist system discussed in [3] and [4]. It requires distances and relative speeds between three vehicles on the road and the lateral position on the road for at least one vehicle. In order to use the RMUs for this purpose, they hence need to be able to estimate vehicle parameters such as speed, type, as well as lateral position.

Given that such an estimation yields good results, an infrastructure-based overtaking assist system can be designed. It can be shown that the detection range for an oncoming vehicle can be as large as 750m, in certain worst cases, [4]. This also means that stand-alone on-board systems are virtually impossible to design without external information. A prerequisite for an overtaking assist system is the estimation of vehicle speeds. Vehicle speed estimation has interested the research community for quite some time and a recent example, using an array of microphones, can be found in [5]. But due to the construction and placement of the RMUs, this approach is not feasible here, since our considered approach requires surface mounted sensors.

Additionally, approaches to detect vehicles and estimate vehicle speeds based on a magnetic sensor setup is also frequently considered. Usually, these systems can be mounted on the surface and integrated into small units, see [6, 7, 8]. The fundamental feature of these schemes is to detect the change in the magnetic field due to the presence of a magnetic mass in the perimeter of the sensor. This means that even stationary vehicle could be detected. Still, any of the proposed solutions to estimate the velocity of vehicles require two sensor sources with known displacement, and near perfect synchronization.

To complement these schemes, the purpose of this paper is to focus on estimation algorithms that are based on road surface vibrations which are measured using a 3-axes accelerometer. The aim is to investigate the possibility to construct a stand alone sensor node overcoming the difficulties expressed above. Furthermore, it is our belief that such a solution is more robust to weather phenomena. As such this paper is an initial investigation showing some of the features that we are currently able to extract. Our final aim is naturally to identify critical parameters such as vehicle speed, vehicle type, as well as lateral position.

EXPERIMENTS

In the final production layout the RMU is glued to the road surface in accordance with Fig. 1. This means that any sensors that are integrated into the RMU have a close contact to the road surface and any vibrations in the road surface are also transmitted into the casing.

In order to get initial insights into vehicle-excited surface vibrations, data is acquired by an accelerometer with large bandwidth and high resolution. This also renders additional design freedom as the limitations and restrictions of a production solution are not limiting the view on studied phenomena. Clearly, production hardware could be simulated with the help of sensor models and then the effect of the limitation on the performance assessed.

For the considered measurements, the sensor is aligned with the road such that the x-axis and y-axis are in the lateral and longitudinal direction of the road, respectively. The z-axis is simply the vertical direction. In that way three components of the vibration wave can be registered simultaneously. The experimental setup is depicted in Fig. 2. There, the road surface is indicated by number 1 and the ice on the surface by number 2. The numbers 3 & 4 show the position of two 3-axes accelerometers and number 5 houses a magnetic sensor. The magnetic sensor in the setup is used as secondary measurement for comparison.

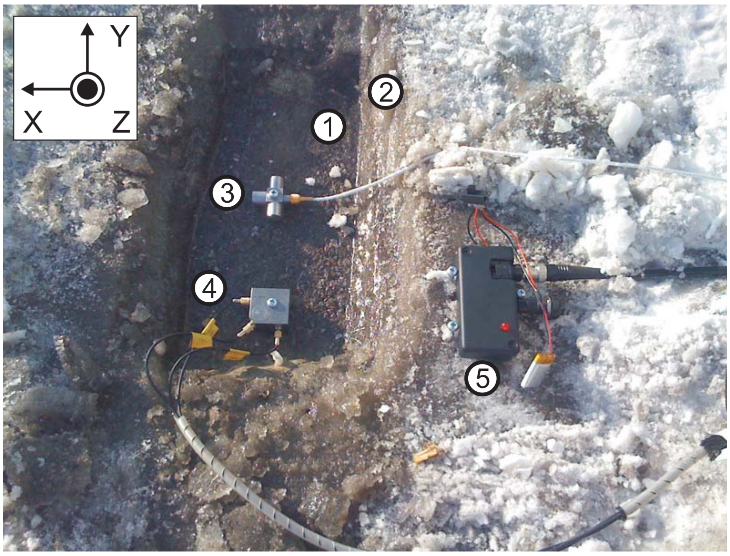

Figure 2 – Experimental setup for the acquisition of the measurement data on the road. The picture is taken during winter time with an icy road surface.

The vibrations that are registered by the sensor depend on several factors, vehicle dynamics, road unevenness and road flexibility, see [9]. The load of the vehicle is accounted for in the vehicle dynamics. These factors can be combined into a model for the dynamic axle load which is derived in [10]. The model depends on additional factors like lateral distance between vehicle and sensor and the vehicle speed, which are of interest in the estimation.

It is therefore necessary to conduct different kinds of experiments that provide information on how road properties as well as vehicle properties are reflected in the registered vibrations. First of all, initial experiments in a controlled environment are conducted to confirm that vehicle speed and distance of the vehicle to the sensor are contributing factors and that a vehicle can be detected properly. These experiments are conducted on a minor road with very small traffic volume and only one sensor source (number 3 in Fig. 2). In several runs a vehicle of type Peugeot 307 is passing by the sensor at speeds 30, 50 and 70km/h. The lateral distance to the sensor at the time of passage was approximately either one meter or five meters. The distances represent a passage in the same lane as the sensor is placed or in the second lane with respect to the sensor.

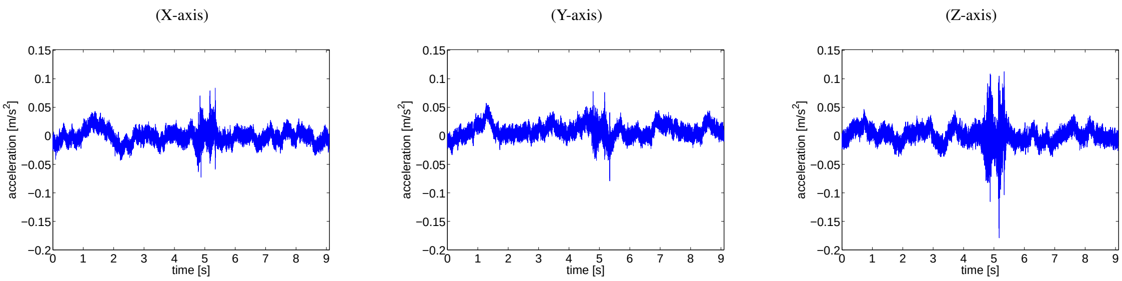

Figure 3 – Time plot of the vibrations registered by the sensor for a vehicle passing at 30km/h

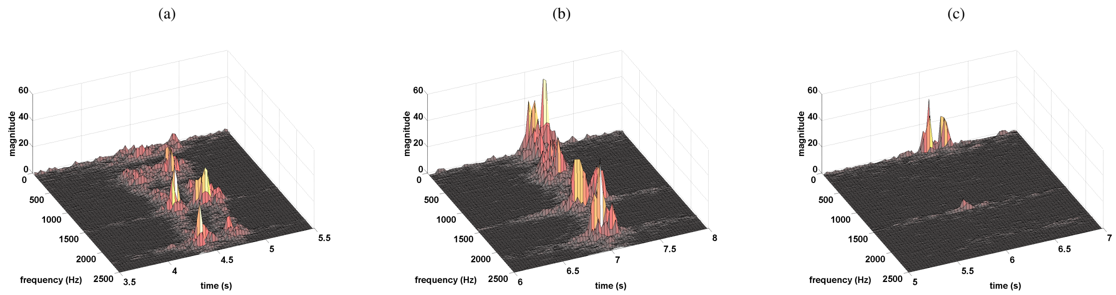

Figure 4 – Power spectral density of the vibration signal over time for a vehicle passing by: (a) 30km/h, (b) 70km/h (c) in the second lane.

An example for the acquired time-domain measurement data is given in Fig. 3 for a passage with a speed of 30km/h. The depicted data is raw and unfiltered. Obviously, the three channels have different behaviour and intensity. From visual inspection it can be concluded that the z-axis is the dominating channel which relates to the primary wave, but all three channels show significant changes in the vibration pattern when a vehicle is passing.

An estimate of the short time power spectral density for the z-channel is shown in Fig. 4 (a)-(c). In the cases (a) and (b) the vehicle passed by the sensor at the close distance of approximately one meter and in (c) at the longer distance of approximately five meters. During passage, we notice significant contributions at harmonics of approximately 725Hz. Furthermore, from visual inspection we can identify two peaks in Fig. 4a, corresponding to each of the axles of the vehicle. This indicates that automatic vehicle detection and wheel base estimation can be achieved.

Both cases (a) and (b) consider data collected using a passage in the nearby lane. Since the sensor is also measuring information from lanes further away a natural question is, if an estimation scheme can distinguish between sources that are close or farther away from the sensor. In order to perform a correct traffic assessment, individual lanes should be addressed.

In Fig. 4c, the power spectral density over time for a vehicle in the second lane is depicted. This vehicle was passing by with 50km/h. It can be seen, that the vibrations are completely attenuated for certain frequencies. Therefore by studying frequency characteristics, the concept can be used to conduct traffic assessment on the lane-level by placing the units on the road sides. For a 2+2 or a 2+1 road configuration this means that the sensors would need to be placed at the right lane marking of the first lane and at the left lane marking of the second lane. If the third and fourth lane (opposite direction) are very close to the first two lanes and if the asphalt is not interrupted, there might be a disturbance effect from the third and fourth lane. In the worst case, this would yield a false detection in the second lane.

In a real-life setting, the traffic volume is usually much larger and vehicles are traveling at different inter-vehicle distances, distances to the sensor, and speeds. Any estimation scheme for vehicle properties need to be robust to these variations. The second kind of experiments are therefore conducted on a road with rather high traffic volume and high average speeds. The speed limit on the road is 90km/h and it is expected that vehicles and trucks pass by at speeds both above and below the limit. Additionally, some of the passing vehicles will have a large number of axles due to trailers.

Data from these experiments are used to both evaluate and design estimation schemes and will be discussed more in further detail in succeeding sections. It is also important to note that the first experiments were conducted when the pavement was still at non-freezing temperatures and the second experiments in the real-life setting were conducted during winter time where the pavement was well below zero degrees. This should affect the road flexibility, but has not been further investigated during this work.

METHOD DESCRIPTION

Seismic waves caused by any form of excitation propagate as body waves in the earth (p- and s-waves) and along the surface (Loeve and Rayleigh waves). Depending on the way of propagation, the waves undergo different attenuations. Surface waves spread circularly in two dimensions and are subject to an attenuation of $1/\sqrt{r}$ whereas body waves are attenuated by $1/r$ in a homogeneous medium [11]. P-waves and Loeve waves cause longitudinal and horizontal motion respectively and thus basically contribute vibration components to the x- and y-directions (see Fig. 5). The s-wave applies transverse stress and the Rayleigh wave horizontal transverse stress to the ground and are therefore the main cause for vertical vibrations (z-direction). Furthermore, it has been shown that vibrations originating from close to the surface carry about 2/3 of the energy in the surface wave and only 1/3 propagates as body waves [12]. To exploit these features, analysis is performed on the vibration component normal to the surface.

As shown in the previous section, the vibration signal is a broadband signal with several predominating frequency components. Some research has been done on low frequency components [13, 14]. In this work however, we focus on the higher frequency components in the band between 900Hz and 1750Hz. The generally lower energy in this band causes spatial filtering in the sense that sources farther away (*e.g.* on the second lane) cause less to no vibrations at the point of measurement. Furthermore, better separation and less disturbances from other sources than vehicles (*e.g.* nearby construction work) can be expected in this frequency region.

Based on these motivations, the fundamental problem, vehicle detection and axle counting is addressed. It can be used for simple traffic monitoring and gathering basic statistics but it can also be seen as the starting point for all other parameter estimations. The number of axles

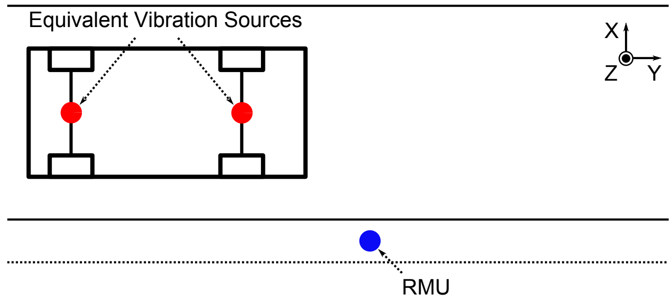

Figure 5 – Illustration of the equivalent point sources model and the setup on the road

and their positions relative to each other help to gain important knowledge about passing vehicles. Therefore, a model-based approach for axle estimation using the energy envelope of the vibrations is proposed.

When examining a vehicle moving along the road, one can assume that the road vibrations are caused by M equivalent point vibration sources where M represents the number of axles as illustrated in Fig. 5 [15]. Accordingly, vibrations originating from the different sources reach the sensor node with a time delay t_d depending on the wheel base (spatial separation of the sources) and the vehicle velocity. This can be exploited to separate the incoming pulses to determine the number of axles.

The vibration characteristics for one axle can be described by a wavelet $p(t)$, which is a combination of vibration components caused by the vehicle construction as well as the pavement response. For M axles, the measured vibrations then become a superposition of time-delayed and stretched pulses

$$z(t) = \sum_{i=1}^{M} A_i \cdot p(a_i \cdot (t - t_i)) + e(t) \tag{1}$$

where A_i is the damping factor, a_i the stretching coefficient determining the pulse width and t_i the pulse delay for the i^{th} pulse. The signal is also disturbed by the error component $e(t)$.

The measured signal $z(t)$ is bandpass filtered to limit the signal to the frequency band specified earlier and then squared to calculate the power signal. Finally, a cumulative sum over the last K energy values is calculated to extract the signal's envelope $s(t)$ (see Fig. 6).

A model-based approach is used to determine individual pulses $g(t)$ in the envelope $s(t)$. It is obvious that the choice of the model is crucial for the performance, accuracy and validity. A natural pulse shape to consider is the Gaussian bell curve as shown in (2). This model is supported by the observation of the vibrations in time domain as well as the energy envelope as shown in Fig. 6.

$$g(t) = \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} \tag{2}$$

Thus, for the most common case, vehicles with two axles, the energy envelope can be approximated as

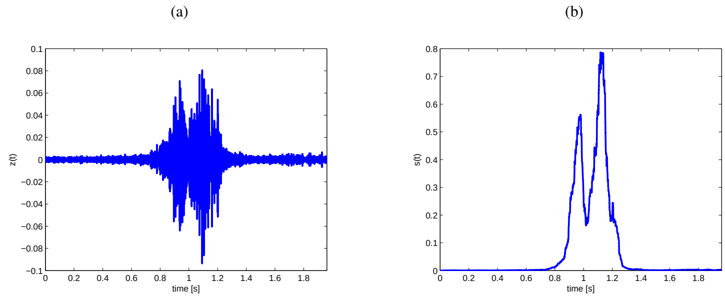

Figure 6 – (a) Measured and band-limited vibration signal for a delivery truck and (b) the extracted energy envelope

$$\begin{aligned} s(t) &= B_1 \cdot g(b_1 \cdot (t - t_1)) + B_2 \cdot g(b_2 \cdot (t - t_2)) + n(t) \\ &= \frac{B_1}{\sqrt{2\pi}} \cdot e^{-\frac{(b_1 \cdot (t-t_1))^2}{2}} + \frac{B_2}{\sqrt{2\pi}} \cdot e^{-\frac{(b_2 \cdot (t-t_2))^2}{2}} + n(t) \end{aligned} \tag{3}$$

with the noise component $n(t)$.

Based on the fact that both pulses are caused by the same vehicle and therefore have the same input parameters (*e.g.* vehicle speed) due to mechanical coupling, one can assume that both pulses have the same pulse width, *i.e.* $b_1 = b_2$. This assumption simplifies the model in (3) slightly and reduces the problem of fitting the model by one variable.

To estimate the modeled energy distribution $\hat{s}(t)$ in (3) using the measured $s(t)$, the least-squares fit [16] is applied and the minimization problem becomes

$$\begin{aligned} J(\boldsymbol{\lambda}) &= \sum_t \left(s(t) - \hat{s}(t, \boldsymbol{\lambda})\right)^2 = ||s(t) - \hat{s}(t, \boldsymbol{\lambda})||_2^2 \\ \hat{\boldsymbol{\lambda}} &= \arg\min_{\boldsymbol{\lambda}} J(\boldsymbol{\lambda}) \end{aligned} \tag{4}$$

The parameter vector $\boldsymbol{\lambda}$ that is subject to the minimization is a 6 element vector of the form

$$\boldsymbol{\lambda} = \begin{bmatrix} B_1 & B_2 & b_1 & b_2 & t_1 & t_2 \end{bmatrix}$$

Note that the problem is linear in B_1 and B_2 and therefore can be reduced to an optimization problem with 4 parameters [16].

Due to the fact that the number of axles M varies depending on the vehicle, it is difficult to estimate the whole signal at once. Therefore, using a fully parametric approach, the number of axles needs to be determined first. Since this is a difficult task, especially for small differences in t, we chose another approach. Here an iterative fitting is used where one pulse is estimated at a time. The residual is calculated by subtracting the estimated pulse from the measured signal and the next pulse is estimated using the remaining signal. The advantage of this method is the reduction of the fitting problem to three parameters at a time which makes the estimation presumably faster. One major drawback is the fact that this approach will yield bigger errors for heavily overlapping pulses that occur at high velocities.

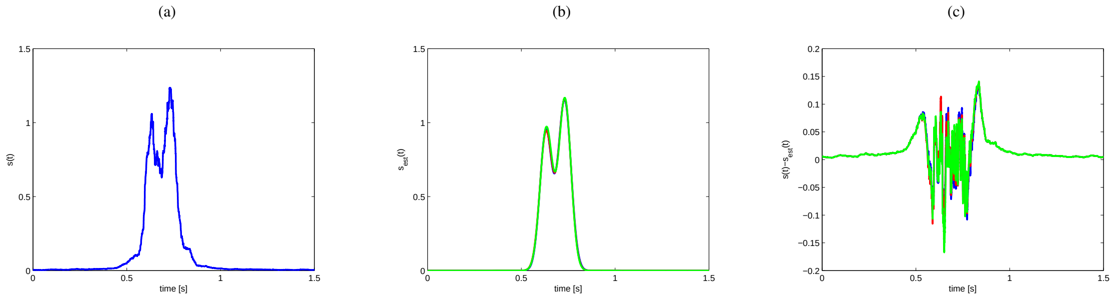

Figure 7 – Estimation results for a passenger car at a speed of 28m/s: (a) Signal envelope, (b) estimate and (c) error.

In this iterative approach, the estimated pulse per iteration reduces to

$$s(t) = B \cdot g(b \cdot (t - t_d)) + r(t) = \frac{B}{\sqrt{2\pi}} \cdot e^{-\frac{(b\cdot(t-t_d))^2}{2}} + r(t) \tag{5}$$

where $r(t)$ represents the residual signal including disturbances. The minimization criterion remains the same as in (4) but has to be minimized for each iteration. The parameter vector becomes

$$\boldsymbol{\lambda} = \begin{bmatrix} B & b & t_d \end{bmatrix}$$

for each iteration.

RESULTS

To evaluate the performance of the proposed method for vehicle counting and axle estimation, it is applied to measurement data captured as described before. The three different variants, one-pass, one-pass with one pulse width and iterative fit are tested and compared.

Fig. 7a shows the envelope for a passenger car where the two peaks clearly show the car's two axles. The car's velocity was approximately 28m/s[1]. In Fig. 7 (b)-(c), the estimations and their errors are shown, respectively. One can see that all the estimations perform similarly as there is no observable difference in the envelope estimates (Fig. 7b) and the error signal reveals only small deviations (Fig. 7c). This is also supported by the resulting residuals as presented below where $\hat{\boldsymbol{\lambda}}_1$, $\hat{\boldsymbol{\lambda}}_2$ and $\hat{\boldsymbol{\lambda}}_3$ represent the estimated parameter vectors for one-pass, one-pass with one pulse width and iterative fit respectively.

$$J(\hat{\boldsymbol{\lambda}}_1) = 38.4$$
$$J(\hat{\boldsymbol{\lambda}}_2) = 39.0$$
$$J(\hat{\boldsymbol{\lambda}}_3) = 40.4$$

[1]The approximate velocity was calculated using the video taken during the measurements. The velocity could not be determined exactly due to several uncertainties such as the parallax error.

As expected, the one-pass estimation performs best. The difference to the other methods on the other hand is not large as the residual norm shows. Therefore, the differences can practically be neglected.

When considering the time difference between the two pulses, we can calculate the wheel base based on the assumed vehicle velocity. This yields reasonable results for each of the three methods and matches the approximate wheel base of 2.7m as determined using the video.

$$\begin{aligned}
b_1 &= (1.231s - 1.131s) \cdot 28m/s = 2.80m \\
b_2 &= (1.232s - 1.132s) \cdot 28m/s = 2.80m \\
b_3 &= (1.232s - 1.133s) \cdot 28m/s = 2.77m
\end{aligned}$$

The estimation procedure becomes more difficult as the pulses overlap more, *e.g.* due to higher velocities or very short wheel bases as it may occur for trucks with double-axle bogeys. Different problems become apparent in such situations, *e.g.* that the pulse might tend towards a much wider single pulse in which case the whole pulse can be approximated by just one pulse and the second pulse converges to some noise peak for the standard passenger car problem. This, however, can be overcome by choosing a well-defined set of constraining functions regarding the pulse width and height.

So far, we have limited our study to vehicles with two axles. In real world situations however, the number of axles is not known a priori and a strategy for iteration is required. This may be achieved by *e.g.* extending the introduced iterative method to M pulses or sparse estimation [17]. Furthermore, the problem of assigning an axle to a vehicle might be ambiguous, especially in cases where vehicles happen to have long wheel bases such as trucks with trailers.

The results have shown that our method can be used to estimate axles of a vehicle. It became also apparent that there is a duality between vehicle speed and wheel base. Knowing either of these two parameters will help us finding the second by combining it with the results of the presented method.

CONCLUSIONS

In this paper we have shown the application for intelligent road infrastructure using low-cost and low-power sensor nodes to measure and estimate vehicle parameters based on road surface vibrations. Experiments showed that these vibrations can be exploited to extract basic properties. Furthermore, a simple method for vehicle and axle detection based on the local energy estimation was introduced as a first application and discussed.

The results show that it is feasible to process seismic waves caused by vehicles and measured by a single accelerometer for the estimation of vehicle parameters. The number of axles was successfully calculated using the energy envelope and the wheel base could be deduced. Limitations of the chosen approach were also discussed and alternatives were presented.

In future work, the road vibrations will be analyzed more thoroughly to exploit other features. The aim is to completely characterize traffic, including vehicle velocity, lateral position and vehicle classification at one node. Thereby, one of the cornerstones for a cooperative road infrastructure will be created and becomes available.

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