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On the Feasibility of Road Vibrations-based Vehicle Property Sensing

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Abstract

This paper discusses a novel approach to vehicle property sensing based on traffic induced road surface vibrations and investigates the feasibility of this approach. Road surface vibrations from real-life experiments are acquired using 3-axis accelerometers and the data is analyzed. Based on the assessment of the data, a first coarse scheme for axle detection of passing vehicles is developed. The scheme is then evaluated using measurement data from a highway with moderate traffic intensity but diverse traffic. It is found that the proposed approach is feasible and the estimation scheme yields promising results. Furthermore, delimitations, encountered problems and identified research challenges are discussed and future research directions are given.

Keywords: Road surface, accelerometer, vehicle detection, traffic counting, axle parameters, traffic induced vibrations, surface mounted, sensor node

1 Introduction

Fatality in road traffic is the dominating cause for non-natural human death in our societies, [2]. Traffic accidents are the main cause of death in the under 45 age group and here alone cause more deaths than heart disease or cancer. Furthermore, the annual cost related to traffic accidents is estimated to exceed 160 billion Euro per year, which corresponds to 2% of EU GNP, [2]. Adding cost for general traffic problems, e.g. traffic jams, increases the cost by 3%. Thus, there is a big potential for reducing costs and saving lives by making road traffic safer. There are many ways to address this problem, e.g. by adding new safety features to cars in order to assist the driver in taking decisions and to prevent harmful situations [3, 4]. Currently, the most promising efforts make infrastructure and vehicles more intelligent and in the future more integrated. The integration is achieved by sharing information between different units and by cooperating directly to reduce negative traffic effects.

Naturally, this cooperation involves vehicle-to-vehicle (V2V) communication and vehicle-to-infrastructure (V2I) communication. Current research projects, like CVIS [5], Coopers [6] and Safespot [7], have already established the necessary standards and information infrastructure in order for vehicles and infrastructure to cooperate. The main information source of such systems are sensors mounted either on-board or situated in the near road infrastructure. Currently, both approaches have shortcomings. In order to achieve significant performance for the V2V scenario, a large share of vehicles needs to be equipped with transponders. This will take a long time to attain. In the V2I scenario, reliable infrastructure based sensor technologies are usually very expensive and in order to be effective it needs to reach a large geographic coverage. In [8] it is indicated that the latter issue has a significant effect on the cost benefit urging the need for cost-efficient sensing solutions.

A viable approach is to make the road surface intelligent and equip it with self-sustained wireless sensor nodes. These nodes jointly measure and infer vehicle and traffic parameters and

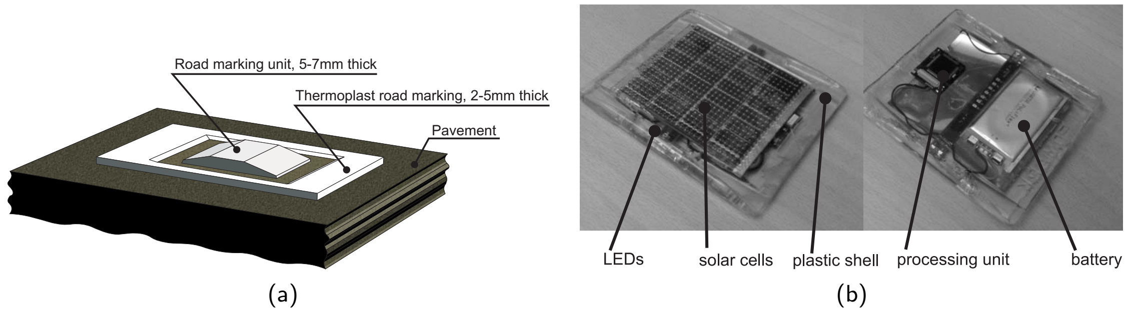


Fig. 1: (a) Schematics and (b) prototype pictures of a road marking unit with integrated electronics (bottom).

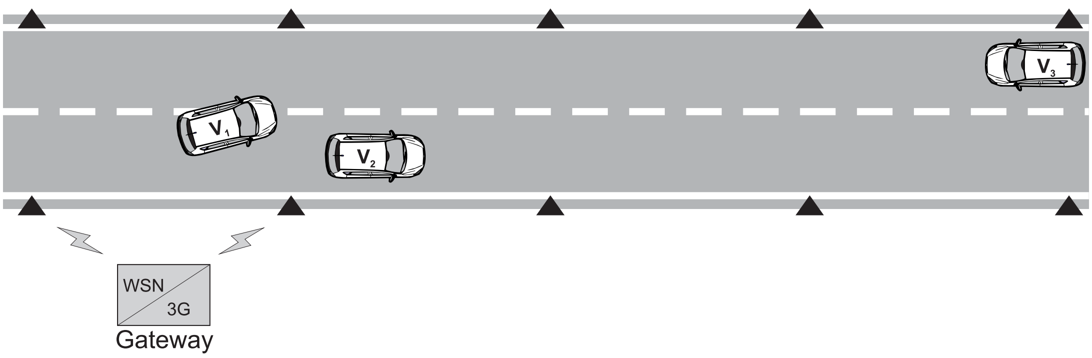


Fig. 2: Example of a road strip equipped with RMUs (depicted as Δ) and their common gateway.

communicate with each other as well as other endpoints such as vehicles and other infrastructure elements [9]. Since the nodes are to be self-sustained, they depend on a scarce energy budget. Therefore, it should be noted that a trade-off between estimation accuracy, complexity and energy consumption has to be made. The approach taken in this work is to integrate the sensor nodes into the road markings, hereafter denoted road marking units (RMU). An illustration of an RMU is shown in Fig. 1. We note that the sensing range of an RMU is very limited to its vicinity. Much like well established traffic sensors, it characterizes traffic within a local neighborhood of a few meters around the sensor node. Fig. 2 shows how a future road equipped with a set of RMUs could be realized. Each RMU (Δ) measures traffic locally but it is the collected information of many RMUs that enables traffic characterization and tracking on long road strips. Furthermore, RMUs can be connected to the outer world using an access point which acts as a gateway, so that for example other infrastructure elements can access the data.

Recent research results indicate that cost-efficient sensors suited for such sensor nodes can be developed for the purpose of estimating vehicle and traffic data. As an example, approaches to detect vehicles and estimate vehicle speeds based on magnetic sensors are frequently considered. Usually, these systems can be integrated into small units and mounted on the surface as described above [10, 11, 12]. The fundamental feature of these schemes is to detect the change in the earth's magnetic field due to the presence of a magnetic mass in the perimeter of the sensor. This means that it is possible to even detect stationary vehicles. Still, for full effectiveness this approach has some limitations that need to be overcome. As an example, any of the proposed solutions to estimate the velocity of vehicles requires two sensor sources with known and accurate displacement and near perfect synchronization.

To complement these schemes, the purpose of this paper is to focus on estimation algorithms that exploit road surface vibrations which are measured using a 3-axes accelerometer. The aim is to investigate the possibility of exploiting vehicle induced vibrations for parameter estimation in order to construct a stand alone sensor node as described. It is our belief that such a solution is inexpensive and also more robust to weather phenomena as compared to other sensors such as roadside cameras or radar.

Additionally, it has to be understood which information the RMUs are required to provide. Depending on the application, the necessary parameters can differ largely. A first step is to identify the sources of the vibrations, the vehicle's axles. If individual axles can be detected in the measured vibrations, they will be the base to estimate further parameters. For example, (1) vehicle speed, (2) acceleration and (3) lateral position are interesting parameters in terms of traffic safety and management functions. Other properties such as (4) trailer detection, (5) vehicle type and (6) wheel base are important for vehicle classification or road maintenance. As such, this paper reports the current status about the feasibility of vehicle parameter estimation based on road surface vibrations. Experiments for the acquisition of traffic vibration data used for analysis and method development are described first. This is followed by the axle detection method description and finally, the results are presented and discussed thoroughly. Concluding remarks summarize the work and give an outlook to future research.

2 Experiments

2.1 Measurement Method

In the final production layout, an RMU is glued to the road surface in accordance with Fig. 1. This means that any sensors that are integrated into the RMU will have close contact to the road surface and any vibrations in the road surface are also transmitted into the casing. However, in order to get initial insights into vehicle-induced surface vibrations, data is acquired by an accelerometer with large bandwidth and high resolution directly mounted on the road. This also renders additional design freedom as the limitations and restrictions of a production solution are not limiting the view on the studied phenomena. Clearly, more limited sensors can be simulated with the help of sensor models and then the effect of the limitation on the performance can be 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 the vertical direction. In that way three components of the vibration wave are registered simultaneously. The experimental setup is depicted in Fig. 3.

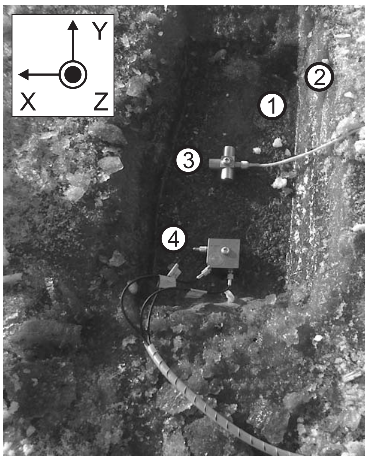


Fig. 3: Experimental setup for the acquisition of the measurement data on the road with (1) road surface, (2) ice layer and (3) & (4) accelerometers. The picture is taken during winter time with an icy road surface.

The vibrations that are registered by the sensor depend on several factors. Road unevenness, road flexibility and vehicle load can be combined into a model for the dynamic axle load on the road [13, 14]. Additional factors like lateral distance between the wheel and sensor or vehicle speed are included in the vehicle motion, which are the parameters 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. 3). In several runs a vehicle of type Peugeot 307 is passing by the sensor at speeds 30km/h, 50km/h 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 location or in the second lane with respect to the sensor.

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 needs to be robust to these disturbances. The second experiment is 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 design and evaluate estimation schemes and will be discussed more in detail in the succeeding sections. It is also important to note that the first experiment was conducted when the pavement was still at non-freezing temperatures and the second experiment was conducted during winter time where the pavement temperature was well below zero degrees. This affects the road flexibility, but has not been further investigated during this work.

2.2 Measurement Assessment

An example for the acquired time-domain measurement data is given in Fig. 4 for a passage with a speed of 30km/h. The depicted data is raw and unfiltered. Obviously, the three channels have different behavior 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.

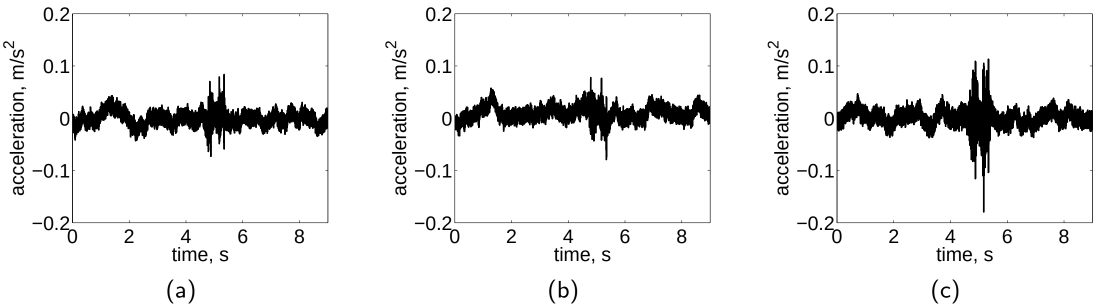
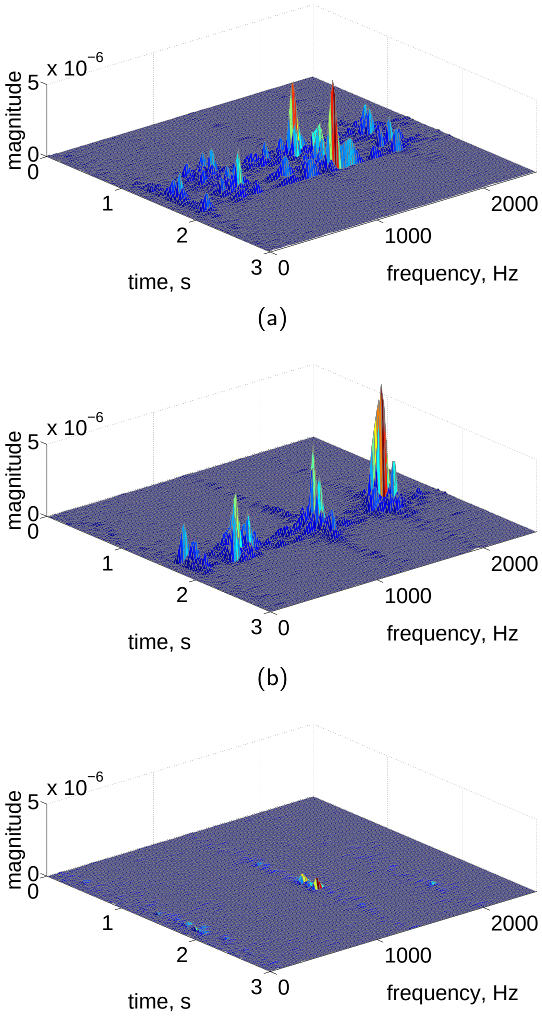


Fig. 4: Time plot of the vibrations registered by the sensor for a vehicle passing at 30km/h. (a) X-axis, (b) Y-axis and (c) Z-axis.

An estimate of the short time power spectral density for the z-channel is shown in Fig. 5. 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, we can identify two peaks in Fig. 5a, presumably corresponding to each of the axles of the vehicle.



(a)

(b)

(c)

Fig. 5: Power spectral density of the vibration signal over time for a vehicle passing by at (a) 30km/h in the fist lane, (b) 70km/h in the first lane and (c) 50km/h in the second lane.

Both cases Fig. 5a and Fig. 5b consider data collected using a passage in the nearby lane. Since the sensor is also measuring information from lanes farther away a natural question is if an estimation scheme can distinguish between sources that are close or far away from the sensor. In order to perform a correct traffic assessment, individual lanes should be addressed. In Fig. 5c, the power spectral density over time for a vehicle passing by with 50km/h in the second lane is depicted. It can be seen that the vibrations are almost completely attenuated for certain frequencies. This is an indicator for the higher attenuation due to the longer propagation distance from the second lane to the sensor.

3 Method description

Based on the findings shown in the previous section, it is here shown how road surface vibrations can be exploited to detect vehicle axles.

3.1 Seismic Waves

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

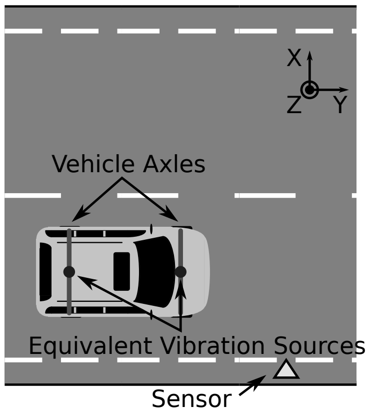


Fig. 6: Illustration of the equivalent point sources model and the sensor on the road.

and are subject to an attenuation of $1/\sqrt{r}$ whereas body waves are attenuated by $1/r$ in a homogeneous medium [15]. 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. 6). 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 [16]. To exploit these features, analysis is performed on the vibration component normal to the surface.

As shown in the previous section, the vibration signal constitute a broadband signal with several predominating frequency components. Some research has been done on low frequency components [17, 18]. 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.

3.2 Model

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 corresponds to the number of axles as illustrated in Fig. 6 [19]. 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 detect the individual axles.

The vibration characteristics for one axle can be described by a pulse $p(t)$, 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 power samples yields the signal's energy envelope $s(t)$ (see Fig. 7).

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.

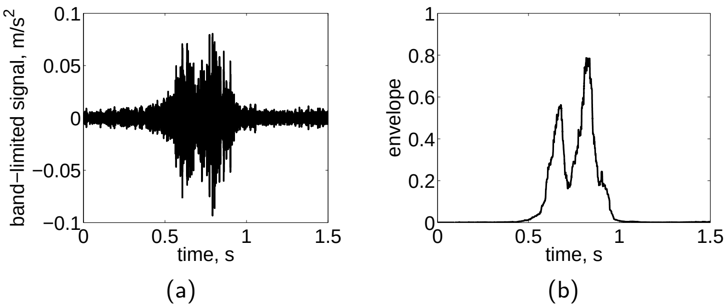


Fig. 7: (a) Measured and band-limited vibration signal for a delivery truck and (b) the energy envelope.

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. 7.

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

Thus, for vehicles with M axles, the energy envelope can be modeled as

$$\begin{aligned} s(t) &= \sum_{i=1}^{M} B_i \cdot g(b_i \cdot (t - t_i)) + n(t) \\ &= \sum_{i=1}^{M} \frac{B_i}{\sqrt{2\pi}} \cdot e^{-\frac{(b_i \cdot (t-t_i))^2}{2}} + n(t) \end{aligned} \tag{3}$$

with the noise component $n(t)$.

3.3 Estimation Methods

To estimate the modeled energy signal $\hat{s}(t)$ in (3) using the measured $s(t)$, a non-linear least-squares fit [20] is applied and the minimization problem becomes

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

The parameter vector $\boldsymbol{\lambda}$ that is subject to the minimization is a $3M$ element vector of the form

$$\boldsymbol{\lambda} = \begin{bmatrix} B_1 ... B_M & b_1 ... b_M & t_1 ... t_M \end{bmatrix}^T$$

Note that the problem is linear in B_i and therefore can be reduced to an optimization problem with $2M$ parameters [20].

Based on the fact that all 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. $b_i = b_j$ for $i = 1, ..., M$ and $j = 1, ..., M$. This assumption simplifies the model in (3) slightly and reduces the problem of fitting the model by $M - 1$ parameters.

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 an alternate approach. Here, 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 larger errors for heavily overlapping pulses that occur at high velocities.

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

$$\begin{aligned} s(t) &= B_i \cdot g(b_i \cdot (t - t_i)) + r(t) \\ &= \frac{B_i}{\sqrt{2\pi}} \cdot e^{-\frac{(b_i \cdot (t-t_i))^2}{2}} + r(t) \end{aligned} \tag{5}$$

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

$$\boldsymbol{\lambda}_i = \begin{bmatrix} B_i & b_i & t_i \end{bmatrix}^T$$

for each iteration.

3.4 Calculating the Wheel Base

When the first axle of a vehicle passes the sensor (i.e. is aligned laterally with the sensor), the second axle is exactly the distance d of one wheel base behind. It takes the time Δt for the second wheel to pass the sensor which is the time that an unaccelerated vehicle with speed v needs to move the distance d. It therefore holds that

$$d = \Delta t \cdot v \tag{6}$$

In other words, the time difference between the two pulses $\Delta t_{12} = t_2 - t_1$ is directly proportional to the vehicle's wheel base with proportionality factor v.

Assuming that the vehicle's speed is known, the wheel base is directly derived from the axle parameter estimation. For the axle pair (i, j) where $i = 1, ..., M-1$, $j = 2, ..., M$ and $i < j$, the wheel base becomes

$$d_{ij} = (t_j - t_i) \cdot v \tag{7}$$

4 Results and Discussion

4.1 Results

To evaluate the proposed method for axle detection, it is applied to measurement data captured as described above. The three different variants, one-pass (denoted "onepass"), one-pass with one pulse width ("onewidth") and iterative ("iterative") are tested and compared.

Fig. 8a shows the envelope for a passenger car (Peugeot 307) where the two peaks clearly show the car's two axles. The car's speed based on the speedometer reading was 50km/h (14m/s). In Fig. 8b and Fig. 8c, 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 and the error signal reveals only small deviations. This is also supported by the resulting residuals. The three methods yield estimation errors of $J(\hat{\boldsymbol{\lambda}}_{onepass}) = 0.56$ for the one-pass, $J(\hat{\boldsymbol{\lambda}}_{onewidth}) = 0.58$ for the one-pass, one pulse width and $J(\hat{\boldsymbol{\lambda}}_{iterative}) = 0.61$ for the

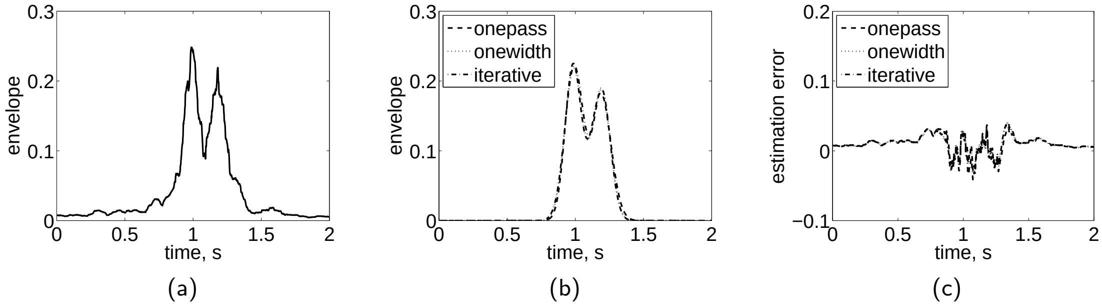


Fig. 8: Estimation results for a passenger car at a speed of 14m/s: (a) Signal envelope, (b) estimates and (c) error.

Vehicle Type	Axle No.	Estimation B_i	b_i	t_i
Passenger Car	1	1.13	27.59	0.680s
	2	2.39	29.41	0.806s
Passenger Car	1	3.06	27.83	1.477s
	2	3.15	37.59	1.581s
Delivery Truck	1	1.40	20.30	1.598s
	2	2.08	29.86	1.735s
Truck with Trailer	1	1.26	19.29	1.208s
	2	3.38	17.85	1.443s
	3	2.48	13.51	1.742s
	4	3.66	16.66	2.116s

Tab. 1: Axle detection results for different vehicles using the one-pass method.

iterative method. The residuals show that the one-pass estimation performs best. The difference to the other methods on the other hand is not large either and therefore, the differences can practically be neglected in this case.

The wheel base calculated from this estimation using (7) and the approximate speed as given above (14m/s) yields:

$$\begin{aligned} d_{12,onepass} &= (1.187s - 0.983s) \cdot 14m/s = 2.86m \\ d_{12,onewidth} &= (1.191s - 0.987s) \cdot 14m/s = 2.86m \\ d_{12,iterative} &= (1.195s - 0.993s) \cdot 14m/s = 2.84m \end{aligned}$$

Comparing this to the actual wheel base of 2.608m for the Peugeot 307 shows that the estimation is biased. This bias can basically be attributed to the inaccuracy of the speedometer reading which is known to be in the order of 10% above the real speed. This confirms that the estimation yields reasonable results.

A brief comparison of the results for four different vehicles is shown in Table 1. From (3) we recall that b_i is a measure for the pulse width. This is mainly affected by vehicle speed, axle load and distance from sensor. Furthermore, it can be shown that the ratio B_i/b_i is equal to the integral of the pulse. This in turn corresponds to the total energy measured by the sensor which is again dependent on the axle load and the distance to the sensor. Considering the results in Table 1, the table indicates that there are essential differences between the different vehicle types. This has, however, not been investigated any further so far.

When applying the proposed methods to the whole data set (135 measured vehicle signatures), the one-pass method yields 78%, the one-pass, one pulse width method 87% and the iterative method 70% valid detections.

4.2 Discussion and Challenges

The purpose of this paper is to serve as a feasibility study in using road vibration for traffic assessment. In contrast to other schemes, using for instance magnetometers, the final aim is not only to detect passing vehicles but also to characterize them. As an initial step, we have within this paper shown that surface vibrations can be exploited in order to extract vehicle axles rather than vehicles. This was achieved using a simple model and crude processing techniques.

Meanwhile, the simplistic approach renders certain limitations. For very fast vehicles or short wheel bases, e.g. trucks with double-axle bogeys, the two pulses overlap significantly. This poses significant challenges for automated algorithms. Furthermore, in order to characterize the number of axles for each vehicle, each axle has to be assigned to a vehicle uniquely. This causes problems in very high density traffic situations where vehicle spacings might coincide with reasonable wheel bases, e.g. for long trucks. More robust and accurate means to extract the involved parameters exist. These include recent work in sparse/convex optimization and data association algorithms [21, 22]. In future investigations we will follow these paths in order to improve the performance of the considered approach.

Meanwhile, the final aim is not only to use the sensing technique for axle counting, but rather use it to exploit more advanced vehicle characteristics, such as vehicle speed, vehicle type, and lane position among others.

As we have already discussed, the results indicate that vehicle and traffic parameter estimation using surface vibrations is a feasible approach. Still many research challenges remain and it is important to identify them and understand both the difficulties and their importance.

Now that the passage of vehicle axles can be detected, the question is if it is possible to determine both vehicle speed and wheel base from one sensor source. Since those parameters are connected according to (7), the time of passage is not sufficient to solve this problem. Axle detection, along with vehicle speed can be used to determine wheel base, an important feature in order to classify vehicles. Meanwhile using similar techniques, the speed of the vehicle can be determined once the wheel base is known. In order to reach our final aim, the duality can be resolved by finding means to extract the vehicle speed using data characteristics other than axle distance. Additional information can be found in the relation between the different sensing directions of the sensor (tri-axial accelerometer) or by adding additional sensors within one road marking unit. Also a combination of both strategies might need to be chosen. Of course the information of a second sensor node could be used as an alternative source too. However, as mentioned before, this introduces new challenges such as increased energy consumption and synchronisation issues. It has also not been discussed what degree of accuracy and repeatability the sensing concepts need to provide, which largely depends on the subsequent usage of the estimates.

From a traffic management perspective, vehicle speed and wheel base are usually two components within the usual traffic counting task that is conducted by road authorities world-wide. Vehicle speed is used as a parameter directly and an accuracy of about 2.5% is requested in Sweden, which is a high level of accuracy. Wheel base on the other hand can be used for classification of vehicles into several categories. In Sweden, there are a total of 15 vehicle classes defined, which are combined into six classes for statistical analysis. There, the distance between the different axles of a vehicle are used as indicators. Here, the difficulty lies in the fact that a vehicle might have more than two axles and that the vehicle has to be identified with its number of axles and their distance between them. Clearly, the estimation of vehicle speed and axle distances with adequate accuracy are a challenge.

From a traffic safety perspective, the lateral distance to the sensor is of importance. This distance can be directly associated with lane departures which can result in unintended roadway departures or in head-on collisions. It has been seen that the intensity of the vibration signal depends largely on the distance to the sensor, which would indicate the intensity is the right choice for the development of a distance measure. But there are more factors, that affect the intensity, especially vehicle speed and axle load. Additionally, it can be assumed that road properties like flexibility, unevenness and construction of the road strip affect the propagation properties of the vibration wave from origin to sensor. Obviously, the phenomena and key parameters that affect the surface vibrations need to be understood and captured in the estimation scheme.

Other complicating factors that affect the estimation of any property are the placement of the sensor relative to the lane and traffic intensity at the installation site. Clearly, traffic in adjacent lanes is a problem as soon as vehicle passages in different lanes contribute to vibrations at one sensing point. This requires either different placement of the sensor so that the positioning solves the interference problem or an estimation scheme that can distinguish the origin of the vibration contributions. Either way, it is still an open question to understand and quantify the problem, and how to addressed it.

Regarding the traffic intensity, it can be assumed that the inter-vehicle distance reduces for a higher intensity, which in turn results in a difficulty to detect individual vehicles. In that sense detection of a vehicle and its classification can become dual. As an example, two passenger cars traveling at close range with the same speed could easily be misinterpreted as a light-weight truck with trailer. Thus, a balance between false detection rate of a vehicle or false classification rate has to be found, which requires a large amount of testing activities.

Although, the list of challenges can become even longer, it is the believe of the authors that the mentioned challenges can be solved and that quantified accuracies for estimates can be derived.

5 Conclusions

In this paper we have shown that it is feasible to process seismic waves induced to the road surface by vehicular traffic to estimate vehicle properties. Based on two experiments where traffic vibrations were measured a rudimentary method for detecting vehicle axles was proposed. The results showed that it is a viable approach to exploit the vibrations and gave valuable insight to the underlying problems.

Naturally, the aim is to further develop the proposed methods as discussed in order to overcome the highlighted challenges. Furthermore, the results encourage to examine the vibrations more thoroughly and eventually, an integration of the new methods into a stand-alone sensor node as described is aspired.

6 Acknowledgement

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