Speeding Detection by Sensing Vehicles: A Simulation Based Evaluation

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ABSTRACT

Speeding is one of the major causes of road crashes. A new speed enforcement management method based on sensing vehicle technologies has the potential to reduce crash migration and to improve traffic safety. The sensing vehicle can detect the speeds of surrounding vehicles and give them warning feedback if speeding is detected. This paper evaluates the performance of the method in the detection stage under different traffic situations. Microscopic simulation in VISSIM and Analysis of variance (ANOVA) are used to examine the performance under various scenarios, including variations of the detection range, number of lanes, speed of the sensing vehicle, traffic flow, average desired speed, and variance of desired speed. The detection range, the speed of the sensing vehicle and the flow of traffic have non-linear effects on the number of detected speeding vehicles. The new method is particularly effective when the traffic flow is moderate with high speed and small speed variance.

Keywords: Speeding, Microscopic traffic simulation, Speed enforcement, Sensing vehicle
INTRODUCTION

Wentao Yang, Erik Jenelius, and Sida Jiang

Speeding, which can be regarded as driving at a speed exceeding the limits (excessive speed) or inappropriately fast for the current conditions within the speed limits (inappropriate speed), is a significant factor in approximately one-third of all fatal accidents (OECD, 2006). Deaths caused by road crashes have reached 1.35 million per year world-wide (WHO, 2018). Apart from the threat to human life, speeding also has environmental impacts since the emissions of both greenhouse gases (typically CO2) and local pollutants (NOx, CO, etc.) are strongly related to this driving behavior (OECD, 2006). Further, quality of life is influenced by the noise caused by speeding, especially in urban areas and during nighttime, and individuals are discouraged to walk or cycle due to the fear of speeding vehicles (OECD, 2006).

Speeding is a common social problem in many countries. Evidence shows that many drivers pay little attention to speeding because they do not consider it a serious traffic offense (Cestac & Delhomme, 2012). From an economical perspective, road users usually ignore the increased fuel consumption and overestimate the travel time saved by speeding (OECD, 2006). Speed management is an important aspect of transport planning. Many studies have highlighted the close correlation between crash frequency, crash severity, and speed (Aarts & Van Schagen, 2006). It is commonly accepted that careful driving can be achieved if drivers are informed of their driving behavior and violations (Rubini et al., 2013). New technologies have been developed, studied and applied to reduce speeding throughout the road networks. Many methods are based on measuring the vehicle speed and warning the drivers.

A widespread method applied in many countries is the implementation of fixed speed detection equipment, such as speed cameras, laser and radar devices. Many studies have verified that the method is effective for reducing the average speed on the road as well as the number of injury crashes and fatal crashes (Wilson et al., 2006). However, there are several issues related to the operation of this method. Firstly, drivers tend to decelerate before meeting a speed camera and then accelerate once they pass it. Therefore, the reduction in speed only happens on a limited road segment (Soole, 2013). Secondly, the cost of operation and maintenance is high. Moreover, fixed speed cameras are difficult to adapt to new traffic situations.

Another method is to combine GPS technology with measuring and warning devices installed inside vehicles, such as intelligent speed adaption systems, geo-fencing or integrated into drivers’ mobile phones, such as driving assistant applications. However, the compliance level to non-compulsory warnings can be low if drivers overestimate their ability to handle the speed. (Warner and Åberg, 2008).

Vehicles equipped with sensors have emerged as a new way of monitoring traffic conditions. One example is the use of GPS data to estimate speed and travel time (Rahmani et al., 2015). Further, vehicle sensors have the potential to enhance road safety (Massaro et al., 2017). This paper proposes a new speed management method based on sensors on floating vehicles (referred to as a sensing vehicle in this research), which can directly give real-time warnings (for example, using an LED screen) to nearby detected speeding vehicles. Assuming that the drivers in speeding vehicles slow down in response to the warnings, the road safety can be enhanced. The sensing vehicles may be allocated in target areas that are exposed to speeding-related accidents.

Compared with traditional methods, the new method is expected to benefit speed management in the following ways. Firstly, instead of measuring the speed of a vehicle at a fixed site, the sensing vehicle continuously detects nearby vehicles over an extended road section. Thus, the compliance duration can be enhanced (Montella et al., 2015). Secondly, the speed
sensor, which is integrated into the sensing vehicle, is economical, since installation and
operation costs are lower compared with wayside fixed cameras. Thirdly, since the sensors are
mobile, the new method makes speed management more flexible and reduces the risk of crash
migration.

To the best of our knowledge, there are no studies on the performance of the sensing
vehicle speed management method. The aim of this paper is to compare and evaluate the
performance of the method under different traffic scenarios, specified as the number of detected
speeding vehicles per sensing vehicle hour. We investigate the impact of several factors: the
detection range, the number of lanes, the speed of the sensing vehicle, the traffic flow, the range
of desired speeds, and the average desired speed. The VISSIM microsimulation tool is used to
generate the traffic scenarios and evaluate the detection performance.

The rest of the paper is organized as follows: The next section presents a literature review
on previous research including speeding behavior, speed detection devices, and speed
management methods. We then present the methodology used in the research, including the
microscopic traffic simulation, data processing and analysis methods. Following that, we provide
the results and discuss the performance under each scenario. The final section concludes the
paper.

LITERATURE REVIEW

Driving behavior of speeding

Many studies have investigated the factors related to speeding behavior. Some drivers are
not aware of whether they are speeding because of inaccurate speed perception, which can be
affected by visual inputs (Gibson, 2014) and auditory inputs (Matthews, 1978). Therefore, the
road environment and noise can affect drivers’ perception of their real speed. Also, transitions
from high-speed zones to low-speed zones lead to a period during which drivers underestimate
their speed (Casey & Lund, 1993).

Based on GPS data accumulated from 152 interviewees, Yokoo and Levinson (2019)
found that drivers tended to speed on long links without many intersections. Siła-Nowicka
(2018) used a GPS-based survey and found that people tended to speed up on main roads such as
motorways or primary roads. In Greece, Kanelladis (1995) collected surveys from both violators
(drivers who claimed not to obey speed limits) and nonviolators (drivers who claimed to obey
speed limits) and found that violators’ speed was primarily influenced by the road layout, while
non-violators were mainly affected by traffic signs. In Australia, Debnath et al. (2014) used
speed data to model speed limit compliance in work zones, and results showed that light vehicles
and vehicles that followed a light vehicle with a large gap were more likely to speed. In Sweden,
Haglund & Åberg (2000) found that a higher compliance level would be achieved if drivers were
given feedback on the proportion of drivers not speeding.

Fixed speed detection devices

The effects of fixed speed detection devices have been studied from different
perspectives. In Belgium, De Pauw et al. (2014) conducted a before-and-after analysis to
compare the effects with varying number of lanes. After the application of fixed speed cameras,
both the average speed and the number of speeding vehicles decreased. However, drivers didn’t
slow down on the segments without cameras. Chen & Warburton (2006) conducted a cost-
benefit analysis to assess whether fixed speed cameras are cost effective. The study found that
the method is beneficial unless travel time values are drastically increased or accident avoidance
is drastically reduced. Høye (2014) applied a meta-analysis to evaluate the effects of fixed
cameras. According to several samples in this research, crash migration, where the number of
accidents increase on other roads, may occur.

To conclude, fixed speed enforcement devices do have a significant effect on the road
segments where they are installed; whilst there are known problems such as crash migration.

**Other speed management methods**

Fixed wayside traffic signs are the basic form of speed management methods. In USA, Wu
et al. (2013) demonstrated that speed limit reductions along with signal warning flashers can
reduce the crash migration problem. Variable speed limit (VSL) systems post speed limits
dynamically based on current traffic conditions. Nissan (2010) applied both empirical methods
and simulation methods to a case study of E4 freeway in Sweden where VSL was introduced. The
compliance level had a strong impact on the effectiveness of the VSL system. Lee & Abdel-Aty
(2008) used a driving simulator to observe drivers’ behavior when passing a VSL sign. A binary
logit model was built to reveal the correlations between the speed limit compliance and adjusted
driving speed. When the speed limit decreased, there was a time lag before drivers decelerated.
However, when the speed limit increased, drivers tended to accelerate immediately to compensate
for delays.

Since extreme weather could make out-of-vehicle speed enforcement warnings difficult to
see, in-vehicle traveler information systems are considered an alternative (Boyle & Mannering,
2004). Regan et al. (2006) found that the performance of intelligent speed adaptation was effective
in reducing mean and maximum speeds as well as the speed variance in most speed zones
according. However, it is difficult to spread the technology unless there is a reduction in the cost.

In Sweden, cooperative systems for intelligent road safety based on infrastructure-to-
vehicle wireless technology have been tested (Böhm et al., 2007, 2009; Farah et al., 2012). These
systems allow exchanges of early warnings between infrastructure and nearby vehicles. The
evaluation indicated an improvement of road safety through increased vehicle gaps and decreased
driving speed.

**METHODOLOGY**

This research evaluates the performance of the new mobile speed detection method under
different traffic scenarios. A sensing vehicle is equipped with a speed sensor. When a vehicle is
following the sensing vehicle within the detection range, the sensing vehicle records its speed and
compares this with the speed limit. We assume that the sensing vehicle only detects speeding
vehicles that travel behind the sensing vehicle with no intermediate vehicles. Thus, vehicles close
to the sensing vehicle but not in the same lane are not counted. Once the following vehicle changes
to another lane, a new vehicle within the detectable range can be monitored (see Figure 1).
In practice, speeding drivers will be notified with a warning message sent by the sensing vehicle once they are detected. According to past research, compliance levels can vary among different warning methods (Shinar & Stiebel, 1986). In this study, the compliance level is limited to zero, which means that the road traffic is assumed not to be distorted by the speeding detection.

The performance of the method is assessed in terms of how many speeding vehicles can be detected by a sensing vehicle during one hour of driving. We define a set of scenarios to investigate how various factors influence the performance: the detection range, the number of lanes, the speed of the sensing vehicle, the traffic flow, the range of desired speeds of the vehicles, and the average desired speed. Table 1 summarizes the scenarios; scenario 1 is regarded as a baseline.

The study is conducted using the VISSIM microsimulation tool. A hypothetical 20 km long straight freeway segment without intersections is set up. This network without turns or intersections captures circumstances under which speeding is common (Yokoo & Levinson, 2019). The speed limit is set to 70 km/h. The driver behavior parameters of VISSIM are set to default values.

Each simulation is run for 60 min. The first 20 min is regarded as a warm-up time to load the road with car traffic. A sensing vehicle is loaded onto the right-most lane of the road segment 20 min after the simulation start. By the time the simulation ends the sensing vehicle has left the freeway segment. The time step is set to 1 s. 15 replications with random seeds are generated for each scenario to produce results with acceptable limited errors (Hansan et al., 2002).
<table>
<thead>
<tr>
<th>Scenario</th>
<th>Number of lanes</th>
<th>Speed of sensing vehicle (km/h)</th>
<th>Traffic volume (vehicle/lane/h)</th>
<th>Average desired speed (km/h)</th>
<th>Traffic speed range (km/h)</th>
<th>Detection range(m)</th>
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<td>60</td>
<td>1000</td>
<td>75</td>
<td>70 80</td>
<td>100</td>
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<tr>
<td>2</td>
<td>2</td>
<td>60</td>
<td>1000</td>
<td>75</td>
<td>70 80</td>
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<td>2</td>
<td>60</td>
<td>1000</td>
<td>75</td>
<td>70 80</td>
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<td>2</td>
<td>60</td>
<td>1000</td>
<td>75</td>
<td>70 80</td>
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<td>60</td>
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<td>75</td>
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<td>75</td>
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<td>75</td>
<td>70 80</td>
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<td>800</td>
<td>75</td>
<td>70 80</td>
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<td>900</td>
<td>75</td>
<td>70 80</td>
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<td>60</td>
<td>1100</td>
<td>75</td>
<td>70 80</td>
<td>100</td>
</tr>
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<td>21</td>
<td>2</td>
<td>60</td>
<td>1200</td>
<td>75</td>
<td>70 80</td>
<td>100</td>
</tr>
<tr>
<td>22</td>
<td>2</td>
<td>60</td>
<td>1000</td>
<td>75</td>
<td>75 75</td>
<td>100</td>
</tr>
<tr>
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<td>2</td>
<td>60</td>
<td>1000</td>
<td>75</td>
<td>72.5 77.5</td>
<td>100</td>
</tr>
<tr>
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<td>2</td>
<td>60</td>
<td>1000</td>
<td>75</td>
<td>67.5 82.5</td>
<td>100</td>
</tr>
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<td>25</td>
<td>2</td>
<td>60</td>
<td>1000</td>
<td>75</td>
<td>65 85</td>
<td>100</td>
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<td>2</td>
<td>60</td>
<td>1000</td>
<td>80</td>
<td>75 85</td>
<td>100</td>
</tr>
<tr>
<td>27</td>
<td>2</td>
<td>60</td>
<td>1000</td>
<td>85</td>
<td>80 90</td>
<td>100</td>
</tr>
</tbody>
</table>

Analysis of variance (ANOVA) is used to compare the detection performance among different scenarios. ANOVA is suitable when comparing the means of multiple scenarios whose responses follow normal and independent distributions (Boyle & Mannering, 2004). When the results of ANOVA show a statistically significant difference among the scenarios, Tukey’s honest significance test (called Tukey’s test in the following) is applied to compare the means of all scenarios (Tukey, 1949). All tests are executed using statistics program R.
SIMULATION RESULTS AND DISCUSSION

Impact of detection range
The detection range of the sensing vehicle is determined by the sensitivity of the installed speed sensors. The appropriate selection of speed sensors depends on the expected performance of the detection and the costs of the sensors. Thus, it is worth investigating whether more vehicles can be detected if the detection range is extended.

In this comparison scenarios 1 to 6, in which only the detection range is varied, are used. The detection ranges vary from 40 m to 140 m in 20 m intervals.

Figure 2 shows the number of detected speeding vehicles per hour (mean value and 95% confidence interval) for each detection range scenario. The p-value calculated from ANOVA is $2.96 \cdot 10^{-10}$, far below the significance level of 0.05. This implies that the null hypothesis of ANOVA that all scenarios have the same performance should be rejected at the significance level 0.05. As the detection range increases, more speeding vehicles can be detected. When the detection range is longer than 80 m, the number of detected vehicles does not increase statistically.

Tukey’s test is used to test the difference in performance between each scenario pair. Table 2 shows that the differences are significant at the 5% level at 40 m, 60 m and 80 m, which means that the performance improves. When the detection range is longer than 80 m, there is no significant evidence that more speeding vehicles are detected. Under the traffic conditions of the scenarios, headways are generally below 80 m. Thus, the detection capability becomes saturated at long detection ranges. For higher traffic densities, a shorter detection range would be sufficient, and vice versa.
Table 2 Tukey’s test results on detectable distances

<table>
<thead>
<tr>
<th>Detectable distance</th>
<th>40 m</th>
<th>60 m</th>
<th>80 m</th>
<th>100 m</th>
<th>120 m</th>
</tr>
</thead>
<tbody>
<tr>
<td>60 m</td>
<td>0.160</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>80 m</td>
<td>0.000*</td>
<td>0.172</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>100 m</td>
<td>0.000*</td>
<td>0.003*</td>
<td>0.702</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>120 m</td>
<td>0.000*</td>
<td>0.001*</td>
<td>0.513</td>
<td>1.000</td>
<td>-</td>
</tr>
<tr>
<td>140 m</td>
<td>0.000*</td>
<td>0.001*</td>
<td>0.471</td>
<td>0.999</td>
<td>1.000</td>
</tr>
</tbody>
</table>

Note: * means that the difference is significant at the 5% level.

Impact of the number of lanes

To determine which road types are suitable for adopting the mobile speed detection and assess the influence of the freeway design on the performance, we vary the number of lanes. We keep other properties of the road, such as lane width, fixed at the VISSIM default values.

In this comparison, freeways with two lanes (scenario 1), three lanes (scenarios 7) and four lanes (scenario 8) in each direction are simulated. The traffic flow per lane is kept constant in every scenario so that higher total traffic flows are loaded on the freeways with more lanes.

Figure 3 shows the number of detected speeding vehicles per hour (mean value and 95% confidence interval) as the number of lanes varies. The differences between the scenarios are small. According to the ANOVA p-value (0.225), there is no enough evidence that more speeding vehicles can be detected when there are more lanes. This is not unexpected given the assumption that only vehicles in the same lane can be detected. This limitation may be reduced if the sensing vehicle can also detect and warn speeding vehicles in other lanes.

![Figure 3 Detection performance as function of number of lanes](image)
The impact of the speed of the sensing vehicle is evaluated by varying the speed from 50 km/h to 70 km/h in increments of 5 km/h (scenarios 1 and 9-12). When the speed of the sensing vehicle increases, the speed difference relative to the traffic decreases. Figure 4 shows the detection performance (mean value and 95% confidence interval) as function of the sensing vehicle speed. Up to 60 km/h, performance improves as the speed increases. Above 60 km/h, meanwhile, the detectable vehicles decrease as the speed of the sensing vehicle increases. The ANOVA shows that the impact of the sensing vehicle speed is statistically significant (p-value $1.11 \cdot 10^{-11}$).

Tukey’s test (Table 3) shows significant differences in performance when the sensing vehicle speed is above 60 km/h, which indicates that performance decreases when the speed of sensing vehicle approaches that of the surrounding traffic. As the speeds become similar, there are less opportunities for overtaking, which undermines the speed detection mechanism. Meanwhile, there are no significant differences when the speed is below 60 km/h, but there is a weak trend that fewer speeding vehicles can be detected at lower sensing vehicle speeds. When the speed of the sensing vehicle is too slow it can act as a disruption to the traffic since other vehicles must slow down to keep a sufficient safety distance. This may cause delays and have negative effects on the experience of other drivers. Thus, speed of sensing vehicle under 50km/h is not tested in this study.
Table 3 Tukey’s test results on sensing vehicle speed

<table>
<thead>
<tr>
<th>Sensing vehicle speed</th>
<th>50 km/h</th>
<th>55 km/h</th>
<th>60 km/h</th>
<th>65 km/h</th>
<th>70 km/h</th>
</tr>
</thead>
<tbody>
<tr>
<td>55 km/h</td>
<td>0.890</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>60 km/h</td>
<td>0.424</td>
<td>0.926</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>65 km/h</td>
<td>0.064</td>
<td>0.005*</td>
<td>0.000*</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>70 km/h</td>
<td>0.000*</td>
<td>0.000*</td>
<td>0.000*</td>
<td>0.004*</td>
<td>-</td>
</tr>
</tbody>
</table>

Note: * means that the difference is significant at the 5% level.

Impact of traffic flow

To analyze how the level of traffic influences detection performance, we vary traffic flows from 300 vehicle/lane/h to 1200 vehicle/lane/h in 100 vehicle/lane/h intervals (scenarios 1 and 13-21). The proportion of vehicles with desired speeds above the speed limit is held fixed in all scenarios. Figure 5 shows the number of detected speeding vehicles per hour (average value and 95% confidence interval) as function of the traffic flow. The ANOVA shows significant differences in performance among the groups (p-value $3.12 \times 10^{-10}$). As the traffic flow increases from 300 vehicle/lane/h, more vehicles can be detected and a maximum is reached between 700 vehicle/lane/h and 900 vehicle/lane/h. The performance decreases when the flow surpasses 900 vehicle/lane/h.

![Figure 5 Detection performance as function of traffic flow](image)

Table 4 shows that differences exist between the 300 vehicle/lane/h scenario and other scenarios, and between the 1200 vehicle/lane/h scenario and other scenarios. Although there is not enough evidence to show statistically significant differences between scenarios from 400 vehicle/lane/h and other scenarios.
vehicle/lane/h to 1100 vehicle/lane/h, there is a clear trend that the number of detected speeding
vehicles first increases and then decreases like a downward parabola. There are two possible
explanations for why fewer vehicles are detected when the traffic volume is low. Firstly, there are
fewer speeding vehicles on the freeway. Secondly, there are fewer overtakings between vehicles
due to long inter-vehicle gaps. In heavy traffic, meanwhile, even though there are more vehicles
on the freeway, the share of speeding vehicles is lower. Thus, fewer vehicles can be detected due
to less opportunities for interaction on crowded roads.

Table 4 Tukey’s test results on traffic flow

<table>
<thead>
<tr>
<th>Flow (vehicle/lane/h)</th>
<th>300</th>
<th>400</th>
<th>500</th>
<th>600</th>
<th>700</th>
<th>800</th>
<th>900</th>
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<th>1100</th>
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</thead>
<tbody>
<tr>
<td>400</td>
<td>0.264</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
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<td>-</td>
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<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>600</td>
<td>0.000*</td>
<td>0.559</td>
<td>0.993</td>
<td>-</td>
<td>-</td>
<td>-</td>
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</tr>
<tr>
<td>700</td>
<td>0.000*</td>
<td>0.111</td>
<td>0.717</td>
<td>0.997</td>
<td>-</td>
<td>-</td>
<td>-</td>
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<td>-</td>
</tr>
<tr>
<td>800</td>
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<td>0.264</td>
<td>0.913</td>
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<td>-</td>
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<td>900</td>
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</tr>
<tr>
<td>1000</td>
<td>0.000*</td>
<td>0.985</td>
<td>1.000</td>
<td>0.993</td>
<td>0.717</td>
<td>0.913</td>
<td>0.692</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>1100</td>
<td>0.176</td>
<td>1.000</td>
<td>0.996</td>
<td>0.692</td>
<td>0.176</td>
<td>0.375</td>
<td>0.161</td>
<td>0.996</td>
<td>-</td>
</tr>
<tr>
<td>1200</td>
<td>1.000</td>
<td>0.147</td>
<td>0.006*</td>
<td>0.000*</td>
<td>0.000*</td>
<td>0.000*</td>
<td>0.000*</td>
<td>0.006*</td>
<td>0.091</td>
</tr>
</tbody>
</table>

Note: * means that the difference is significant at the 5% level.

Impact of desired speed range and average desired speed

We investigate how the homogeneity of the desired speeds of the vehicles affects the
performance of the detection method. In each of five scenarios (scenario 1 and 22-25), vehicles
have uniformly distributed desired speeds within a range that varies from 0 km/h to 20 km/h in 5
km/h increments. In every scenario the average desired speed is fixed at 75 km/h. In scenario 1,
for example, vehicles have desired speeds uniformly distributed from 70 km/h to 80 km/h.

Figure 6(a) shows the number of detected speeding vehicles per hour (mean value and 95% confidence interval) as function of the desired speed range. The ANOVA ($p < 2\cdot10^{-16}$) shows significant differences in the number of detected speeding vehicles for different desired speed ranges. The new method detects more speeding vehicles when the speed range is narrower, which indicates that smaller speed variance of the traffic contributes to better performance. When the speed variance is large, the actual share of speeding goes down.
Figure 6 Detection performance as function of (a) desired speed range; (b) desired average speed.
Table 5 shows that almost all differences between scenarios are statistically significant, except for the comparison between speed ranges 20 km/h and 15 km/h. It can be concluded that the method detects more speeding vehicles when the speed variance is smaller. This is due to more fluent traffic. When speed variance is high there is a larger possibility that a relatively slow vehicle follows the sensing vehicle for a long distance, which results in fewer other speeding vehicles detected.

<table>
<thead>
<tr>
<th>Speed ranges</th>
<th>0 km/h</th>
<th>5 km/h</th>
<th>10 km/h</th>
<th>15 km/h</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 km/h</td>
<td>0.005*</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>10 km/h</td>
<td>0.000*</td>
<td>0.002*</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>15 km/h</td>
<td>0.000*</td>
<td>0.000*</td>
<td>0.023*</td>
<td>-</td>
</tr>
<tr>
<td>20 km/h</td>
<td>0.000*</td>
<td>0.000*</td>
<td>0.000*</td>
<td>0.189*</td>
</tr>
</tbody>
</table>

Note: * means that the difference is significant at the 5% level.

Further, to find out whether the detection performances differs due to the average speed of the traffic, scenarios (scenarios 1 and 26-27) with average desired speeds of 75 km/h, 80 km/h and 85 km/h are simulated. The desired speed range is fixed to 10 km/h.

Figure 6(b) shows the number of detected speeding vehicles per hour (average value and 95% confidence interval) as function of the average desired speed. The ANOVA (p-value $1.3 \cdot 10^{-12}$) shows that there are significant differences. As the average desired speed increases, more speeding vehicles are detected by the sensing vehicle.

Tukey’s test is used to test differences among all scenarios. Table 6 validates the conclusion that, the higher the average desired speed, more speeding vehicles can be detected. When the average speed of the traffic is higher, the speed difference between the traffic and the sensing vehicle is larger, and it is easier for a speeding vehicle to overtake the sensing vehicle.

<table>
<thead>
<tr>
<th>Average speed</th>
<th>75 km/h</th>
<th>80 km/h</th>
</tr>
</thead>
<tbody>
<tr>
<td>80 km/h</td>
<td>0.000*</td>
<td>-</td>
</tr>
<tr>
<td>90 km/h</td>
<td>0.000*</td>
<td>0.000*</td>
</tr>
</tbody>
</table>

Note: * means that the difference is significant at the 5% level.

CONCLUSIONS

This study evaluates the performance of a new mobile sensing vehicle speeding detection method. A microscopic model is built in VISSIM to collect performance data. The performance of the method is assessed under different scenarios, including variations of the detection range, the number of lanes, the speed of the sensing vehicle, the traffic flow, the average desired speed, and the range of desired speeds.

The findings can be summarized as follows:

- There is no need to expand the sensor detection range as much as possible, since the detectable distance reaches a threshold determined by the traffic situation.
The proposed sensing vehicle method is not suitable for application on roads with many lanes, because only vehicles in the same lane as the sensing vehicle can be detected.

When the speed difference between the sensing vehicle and traffic is small, only few vehicles can be detected. Meanwhile, a large speed difference may disturb the traffic negatively.

When traffic is too light, fewer speeding vehicles can be detected. When traffic is too heavy, less freedom for speeding vehicles to overtake and approach the sensing vehicle leads to a limited number of detected vehicles. The method is most effective when applied to a moderate traffic density.

When the range of desired speeds is large, some vehicles that drive a low speed may follow the sensing vehicle for long distances so that no other speeding vehicles can be detected. The method is more effective when the traffic speed is of less variation.

When the average desired speed is high, more vehicles can be detected, because overtaking is easier and more speeding vehicles can catch up with and be detected by the sensing vehicle.

In future research, field experiments are needed to validate the results of the simulation analysis. The compliance level to the management method is regarded as zero in this study. A study on the compliance level can help calibrate the model in a more detailed way. Further, the sensing vehicle is considered to only interact with the speeding vehicle driving right behind in this study. However, a systematic effect on the traffic can be expected. The speed adjustment by warned drivers can lead to a sequence of speed adjustment by other vehicles, which is worthy of further investigation.

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AUTHOR CONTRIBUTIONS
The authors confirm contribution to the paper as follows: study conception and design: Wentao Yang, Sida Jiang, Erik Jenelius; data collection: Wentao Yang; analysis and interpretation of results: Wentao Yang, Sida Jiang, Erik Jenelius; draft manuscript preparation: Wentao Yang. Erik Jenelius. All authors reviewed the results and approved the final version of the manuscript.
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