AN INVESTIGATION OF POSITIONING ACCURACY TRANSMITTED BY CONNECTED HEAVY VEHICLES USING DSRC

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Recent developments in advanced transport technologies such as vehicle-to-vehicle communications and Dedicated Short Range Communications (DSRC) led to an increased interest in building safety vehicular applications that would prevent traffic collisions. Such applications need a high level of performance and positioning accuracy in order to meet critical levels of road safety. However, there is still a lack of practical performance measurements of standard aftermarket DSRC systems, especially on a high number of heavy vehicles operating in large and diverse areas.

This paper presents the results obtained from a research investigation undertaken into the capabilities of current DSRC technology for meeting the positioning accuracy of road safety applications. The available data sets contain almost 400 million Basic Safety Messages (BSMs) transmitted by 58 heavy vehicles equipped with DSRC, operating on a daily basis on a 42 km test-bed area in Illawarra, Australia. Firstly, as ground truth is not available, we conduct a comparative analysis of positioning in the transmitted BSMs by using both Open Street Map and Google Street Map as reference, and show that the latter provides better accuracy in positioning error computation. Secondly, we present the results obtained when analyzing the five most active trucks of the fleet, as well as the noise-prone areas in which false collision alerts were generated. Thirdly, we apply gradient boosted decision trees on the data sets and identify that speed, elevation and heading are the three most important factors that influence DSRC transmitted positioning error in heavy vehicles.

Keywords: DSRC, connected vehicles, gradient boosted decision trees, positioning accuracy.
1. INTRODUCTION

Traffic congestion and road vehicle collisions are one of the most important problems in concentrated urban areas around the globe, leading to almost 1.24 million road traffic deaths per annum (1). Current trends suggest that by 2030 road traffic accidents will become the leading cause of deaths unless urgent action is taken (2). In order to address this issue, intelligent transportation systems (ITS) have become essential in investigating problems of vehicular transportation and improve road safety (3). Advanced transport technologies such as Vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications are already being tested and recent studies show the benefits of adopting these technologies in terms of life-savings and economic impact (4).

Recent advancements in wireless communication technologies have led to the emergence of dedicated short-range communication (DSRC), which has been designed to support V2V communications, enhance mobility and improve road safety (5). As vehicular communications need fast interoperability, U.S., Europe and Japan have assigned dedicated bandwidths for DSRC communications (6). In order to assess the performance and safety benefits of DSRC, various projects and test bed initiatives have concentrated on: testing the effective communication range between two vehicles and security protocols (7), analysing the probability of successful message reception (8), detecting collision situations and sending drivers early alerts (9), analysing collision timing (10), or investigating signal priority for connected vehicles (CV) at signalized intersections (11). Despite a high DSRC reliability indicated by these studies, in 2014, the National Highway Transportation Safety Administration (NHTSA) published the need to further investigate open research problems before establishing rule-making for a deployment-level V2V communication system mandate (12).

One of the biggest problems to address when using DSRC for building safety applications such as proximity collision alerts, automated braking, intersection signal alerts, etc., is to have an accurate vehicle positioning capability. Current systems only use Global Navigation Satellite System (GNSS) (13). Although in ideal operating conditions (clear sky, no obstructions), GNSS can usually meet the positioning accuracy for most DSRC applications, in dense urban areas, high multi-paths or tunnels the GNSS signal can be limited or contains inaccurate positioning (14). Some CV applications need sub-meter accuracy at the lane level, especially for real-time situational awareness (15). Bridging the gap between positioning accuracy and the necessary availability for CV applications represents an important challenge still to be tackled. In (16) the authors proposed a Bayesian approach for using received signal strength data from roadside equipment (RSE) to update and improve GPS positioning. While this approach can work well when RSE is available and ready to use, many test beds have insufficient RSE or they are located at sparse locations throughout the study network. Other studies propose integrating GNSS and navigation information such as map data (13; 17), which contains “metadata” for travellers. However, until such maps are developed and shared across a large fleet, the cost to maintain a huge map database can become prohibitive especially for rapidly growing cities.

Recent research studies have investigated the use of cooperative positioning (CP), which aims to enhance location accuracy of GNSS or to provide position data when GNSS is not available in vehicular ad hoc networks (VANets). CP systems use data fusion methods to combine position-related data transmitted among a group of participating vehicles that can communicate with each other, and thus improve positioning accuracy. While conventional CP systems (differential GPS, real-time kinematic GPS, assisted GPS, etc.) may suffer from limitations such as low signal
coverage, weak signals or accuracy (18), modern CP methods are defined based on vehicle-to-vehicle and vehicle-to-infrastructure communications and are applicable even when GNSS position data is unavailable (19) or when the number of visible satellites is small (20). However, ongoing studies have confirmed that even modern CP systems present constraints in radio ranging/range rating and are not yet capable of bridging the gap and addressing the positioning accuracy required for safety applications, which is under a meter (14). In addition, these models normally require particular sensors with high computational complexity.

While most of the research studies that focus on positioning accuracy problems are undertaken on a small number of vehicles equipped with DSRC and on a limited test area bed, there is a real need for analysing the GPS positioning accuracy transmitted by a large number of vehicles, over a longer period of time and under various traffic conditions. The Cooperative Intelligent Transport Initiative (CITI) is a project currently undertaken by Transport for New South Wales (TiNSW), with the aim of building Australia’s first semi-permanent test-bed for testing the DRSC technology over an area of 917 km² in the Illawarra Region of NSW south of Sydney (21). Currently, sixty vehicles (mostly heavy vehicles), three signalised intersections and one roadside location have been equipped with DSRC units. In order to ensure road safety, one of the main problems of the project is to address the generation of false collision alerts that would hinder driving and might result in drivers ignoring or not trusting the DSRC on-board-unit warning device. The first step to identify the possible cause of false alerts is to investigate and understand the accuracy of the transmitted positioning between the trucks, as reported from Basic Safety Messages (BSMs).

In this paper, we present the procedure, results and analysis we have undertaken in order to investigate and understand the current GPS positioning accuracy of selected DSRC equipped vehicles involved in CITI. The main objectives of this study are:

a) investigating and characterising the error (noise) in the DSRC GPS positioning,

b) identifying “noise – prone sections” of the road network that would cause high levels of noise to be registered,

c) identifying potential factors that would impact noise in the GPS positioning.

In Section 2, we present the CITI project background and main challenges. Section 3 presents the data sources and processing, as well as the map-matching procedure for computing the noise in transmitted GPS. In Section 4, we conduct a positioning analysis and comparison for the five most active trucks selected for this study. We also analyse the most important features that influence noise, as obtained from applying gradient boosted decision trees over the collected data sets. Conclusions and further perspectives of this work are addressed in Section 5.
2. CITI PROJECT BACKGROUND

The Cooperative Intelligent Transport Initiative (CITI) is a project deployed by Transport for NSW (TfNSW) in partnership with Data61/CSIRO and the Australian Federal Government’s Heavy Vehicle Safety Productivity Program. The main goal of the project is to assess V2V/V2I communication technology that could reduce the number of road accidents, with a focus on the Illawarra region. According to TfNSW, 18% of the traffic on Picton Rd (a road in the CITI area) consists of heavy vehicles, which are involved in 63% of fatal crashes (22). In order to address this problem and the high cost generated by truck accidents, CITI project aims at building a semi-permanent test bed for evaluating and further testing of the Cooperative Intelligent Transport Systems (CITS) technology, especially DSRC equipped vehicles.

2.1 Current deployment and location

The focus area for the CITI project represents a 42 km route between Port Kembla and the Hume Highway/Picton Road intersection (Figure 1a). During the first stage, the project has installed DSRC devices in 58 heavy vehicles, 2 light vehicles, 3 signalised intersections (Figure 1b) and 1 roadside unit at the top of Mt. Ousley near Wollongong, NSW. CITI currently utilises Cohda Wireless MK4 and MK5 DSRC (23) units running Cohda’s alert software in vehicles and roadside software for infrastructure deployment. Cohda DSRC systems are using the US standards of IEEE 1609 family, SAE J2735 and IEEE 802.11p standards. The heavy vehicles are usually equipped with 2 MobileMark ECO6-5500 DSRC antennas placed near the mirrors of the trucks, and one MobileMark SM-1575 GPS Antenna often placed in the vehicle, under the dashboard. Software on the units include a dead-reckoning feature. Inside the vehicles, the DSRC unit is connected to a Nexus 7 tablet for audio and visual display of generated alerts, such as Forward Collision Warning (FCW), Intersection Collision Warning (ICW), Electronic Brake Light Warning (EBLW), as well as two custom alerts. The custom alerts are a red light ahead warning based on Signal Phase and Timing broadcasts and a heavy vehicle speed restriction monitoring application that alerts drivers if they exceed a 40km/h restriction on a steep descent in the trial area (21).

![FIGURE 1 a) CITI area with with an example of daily truck trip: (150.558,-34.51) x (151.318,-34.109) (Google maps screenshot). b) DSRC equipped intersections: (150.874,-34.447 x 150.889,-34.439) (Google maps screenshot).]
2.2 Problems and challenges

Currently, there are over 150 drivers from 3 transport companies involved in CITI and some are operating daily trips from Port Kembla near Wollongong NSW to a colliery near Appin, NSW. Many of the truck drivers make up to 7 trips per shift, with the trucks operating in two shifts 24 hours a day, 7 days a week. Vehicles in the trial are broadcasting their position 10 times a second in a message known as the Basic Safety Message (BSM). The positioning information in these messages is based on GPS measurements and if the GPS signal is lost then the position may be extrapolated from last known data in a process known as “dead reckoning” (24). However in CITI, no additional sensors are connected to the DSRC unit and dead reckoning is restricted to interpolations from last GPS locations. For the remainder of this article, reference to “GPS” is actually a reference to “GPS-based positioning information” as broadcasted by a vehicle in a BSM. Therefore, the accuracy of the “transmitted GPS positioning” is not independent of the DSRC unit, but is a mix of processing and transmission methods. Since the beginning of the project, the vehicles have generated more than 400 million BSMs to be analyzed and tested for positioning accuracy.

To date there has been little data analysis for DSRC equipped vehicles operating in CITI. The initial aim is to examine the DSRC positioning performance in the Australian setting, which includes a range of urban and mountain environments, with isolated rural areas and coalmines. Large variations in the transmitted location to other connected vehicles can trigger false collision alerts, or hinder driver response to alerts. As road safety is the main focus of the CITI project, a major concern is to identify the risks that drivers face when exposed to false alarms or when false and correct alarms cannot be distinguished. Therefore, the main objective is to understand how the positioning accuracy of the DSRC equipment deployed in vehicles changes over time and how much the GPS positioning error varies relatively to previously reported locations. This is an important topic to be explored and to understand if the BSM-based GPS data is suitable for conducting further analysis or for detecting changes in the driving behavior when collision alerts are received.

This investigation looks at the noise evolution in locations reported in the BSMs over time, in various places and from various vehicles. In this paper we limit our analysis to the 5 most active trucks in the data sets. As ground truth is not available for identifying the accuracy of the reported GPS location, this investigation uses the closest mapped road position from both Google Street Maps (GSM) and Open Street Map (OSM) to determine the “error” or noise in the DSRC transmitted GPS position. A detailed description of data processing and map matching method is provided in Section 3. As well, another important challenge is to identify the factors that lead to significant errors in the transmitted GPS positioning, based on the available data sets. For this purpose, we apply gradient boosted decision trees and identify the most important factors that can influence noise in GPS positioning, as discussed in Section 4.

3. DATA PROCESSING METHOD

3.1 Data sources and processing

For the purpose of this study, we have received from TfNSW, almost 400 million DSRC messages transmitted by the trucks operating in the CITI project, collected between July 2015 and November 2015. The data was automatically collected from trucks when they stopped near 2 equipped trailers.
It contains all transmitted and received DSRC messages, including BSMs. The final data sets were then collected from the trailers every 2 weeks. After initial data format reading and verification, we batch processed and extracted only the necessary messages and fields for data analysis. In our case, we processed the BSMs containing positioning, speed, heading, acceleration, brakes, elevation, timing, etc.

3.2 Map-Matching

After the positioning points are extracted from the raw positioning data, an important step is to establish the basis for comparison of these positions to “ground truth”. Such a comparison would establish the error/noise in the positioning information broadcasted in the BSM from the true position. Unfortunately a proper “ground truth” – the true position of the vehicle – is not available and very expensive to measure. However, by using Map-Matching (MM) algorithms we can integrate positioning data with spatial road network data (roadway centerlines) to identify the correct link on which a vehicle is travelling and to determine the location of a vehicle on a link (25). Due to the nature of the data sets, we apply a classical post processing map-matching algorithm and emphasize accuracy more than computation efficiency (26). As our main purpose is to be able to identify noise-prone road sections, we focus on the data analysis and noise comparison by using either GSM or OSM for noise calculation, and the regression models for identifying factors that influence noisy GPS observations. While OSM shapefiles for identifying road centers are free to access and use in the MM procedure, in order to map positioning the GPS observations to road centers reported by GSM, we use the Google Snap to Roads API. The mapped positioning points have then been used to compute the Vicenty distance (27) between transmitted GPS locations and GSM.

3.3 Notations and noise calculation procedure

In the following, we denote $D$ as the total number of trucks under the study. For each truck, $d \in \{1, \ldots, D\}$, we have a total number of GPS observations $N_d^{GPS}$ extracted from BSMs. Each GPS observation is described by its location: $x_i = (L_i, l_i), i \in \{0, \ldots, N_d^{GPS}\}$ registered at time $t_i$, where $L_i$ and $l_i$ denote the longitude, and the latitude respectively. The total time travelled by a single truck is denoted by $T_d$, which can contain various trips conducted by the truck over multiple days since the beginning of the trial. Let $\Delta t_i = (t_{i-1}, t_i), i \in \{0, \ldots, N_d^{GPS}\}$ be the time interval between two consecutive GPS observations, which in our case is set to 0.1 seconds, according to the DSRC specifications. Each GPS observation $(x_i, t_i)$ can be mapped to a specific road segment $g_j, j \in \{1, G\}$, which can contain sequential GPS observations with the same spatial-temporal characteristics. A symbolic graphical representation of three consecutive GPS observations over a selected road section is provided in Figure 2.

![FIGURE 2. Examples of GPS observations.](image)
The road section represented in Figure 2 has two lanes in the same direction, and in this case the line separating the two lanes represents the center of the road used for computing the noise. This representation is imposed by the original shape files we have used from Google Street Map and Open Street Map which do not contain the center of each lane, but rather the center of each “direction of travel”, regardless of the number of lanes. Let \( N_i \) be the distance (deviation/noise) between a registered GPS location and the centre of the road section at time \( t_i \), and \( \bar{N} \) the mean noise observed on a selected road section. We also note \( A_i \) as the anomaly detected at time \( t_i \):

\[
A_i = \begin{cases} 
N_i, & \text{if } N_i > 8 \text{ m, } \forall i \in \{1, \ldots, N_d^{GPS}\} \\
0, & \text{otherwise.}
\end{cases}
\]

As the road sections we are investigating have in general 2 lanes, each of 3.5 meters, we consider that any computed distance which is bigger than 8 meters to be recorded as an anomaly in the noise computation. As well, as the truck can be in any of the two lanes, we consider that an \( N_i < 3.5 \text{ m} \) is not considered an error. Therefore, the steps we have applied for detecting noise anomalies for each vehicle, are the following:

1) Consider a road section \([A, B]\) defined by a starting point A and ending point B.
2) Apply a MM procedure for identifying the trajectory of the DSRC GPS positioning.
3) Compute \( N_i \) deviations from the road center for each intermediary points between \([A, B]\).
4) Compute mean deviations (noise) on the selected road section \((\bar{N})\), for all available trips undertaken during the total travel time of a truck \( T_d \).

This procedure has been applied for all heavy vehicles and some selected results will be presented in the following section.

4. POSITIONING ANALYSIS FOR TRUCKS

4.1 Single transmission file analysis

Before presenting the noise results of the trucks, we show the analysis conducted over a single transmission file, belonging to the most active truck, which contains a typical daily trip of a truck from Port Kembla to a nearby colliery, as represented in Figure 1a).

This transmission file contains 87,165 BSMs, recorded between 20:46:13 and 23:12:58 on the 20th of July 2015. For an accurate analysis, we filter GPS positions that indicate stopping in parking areas or inside the mine area. By using GSM as ground truth, we obtain an average noise of 2.9762 meters, with certain GPS points exceeding 8 meters threshold and reaching a maximum of 12.1415 meters from the road center, as represented in Figure 3a) right.

A special area of the selected road section is the Mt. Ousley area (Figure 3b) left) which has a speed restriction of 40 km/h for trucks descending the mountain. Therefore, on this road section the GPS accuracy will generally be obtained at lower travelling speeds. The average noise obtained in this area is lower (2.3836 meters) and the overall noise under 7 meters (Figure 3b) right). The good accuracy in the GPS positioning can be influenced by truck speed, as we will discuss in Section 4. Regarding the continuity of the GPS signal, and the consistency between consecutive GPS points we have observed noise variations that can go up to a maximum of 15cm between consecutive BSMs with \( \Delta t_i = 0.1 \text{ sec} \) (Figure 3c)). While a continuous variation in between consecutive GPS points can indicate that the truck is changing lanes and heading in another
direction, some other variations between registered BSMs seem not to be consistent from previous
ones, and might indicate some deviations in the GPS location transmitted by the DSRC system.

FIGURE 3. a) Noise mapping on selected road section. b) Noise mapping on Mt. Ousley.
   c) Noise variations on Mt. Ousley between consecutive GPS locations from 50 BSMs.
4.1.2 GSM and OSM noise comparison

We apply the same noise computing method by using Open Street Map. Table 1 reports the average and maximum noise level obtained for the single transmission file when using both GSM and OSM.

Table 1 Comparison between GSM and OSM noise for one transmission file example.

<table>
<thead>
<tr>
<th></th>
<th>Google Street Maps</th>
<th>Open Street Maps</th>
<th>Difference [meters]</th>
<th>Error [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Road section</td>
<td>2.9762</td>
<td>12.1415</td>
<td>3.2883</td>
<td>12.6679</td>
</tr>
<tr>
<td>Mt. Ousley</td>
<td>2.3836</td>
<td>7.0131</td>
<td>2.7480</td>
<td>8.0559</td>
</tr>
</tbody>
</table>

These initial results on a single transmission file show a more accurate GPS positioning when using GSM as the “ground-truth”. The average noise when using GSM is smaller than the noise obtained when using OSM. We observe that there is a difference that can vary between 31cm and 36cm between the two pseudo ground truth references, which can influence the final noise results. Based on these initial findings, for the rest of the results presented in this paper we will consider GSM as the ground truth for noise calculation.

4.2 Truck positioning analysis

In this section, we present the data analysis and interpretation we have conducted for the five most active trucks over the selected road section including Mt. Ousley, presented in Section 3. For ease of notation, we denote the trucks as “Truck $i, i = 1,..5$”.

A summary of the total number of investigated BSMs, total dates and detected anomalies for each truck is provided in Table 2. All trucks are coal carriers and are doing daily trips on from Port Kembla to a coal mine near Wollongong. In terms of total number of BSMs, we note that Truck 1 appears to be the most active, with almost 4.75 million BSMs transmitted during the testing period in the Illawarra region, followed by Truck 2. From the total number of transmitted messages, after filtering the BSMs sent on the selected road section, we observe that each truck has different and sometimes unique activity. Truck 2 seems to have a higher transmitting activity in this area, gathering 903,209 BSMs. In terms of detected anomalies, Truck 1 and 2 present again a higher number of deviations from the road center, compared to the last 3 trucks. Truck 2 is the one which registered the biggest number of anomalies, representing 4.69% of its total number of BSM positioning points. As well, on Mt. Ousley road section, Truck 2 has registered 24,234 anomalies (8.65%) compared to Truck 1 (1.08%), which is comparably bigger than the noise recorded for other trucks.
<table>
<thead>
<tr>
<th>Truck</th>
<th>Description of BSM statistics and noise anomalies for each truck.</th>
<th>Start Date</th>
<th>End Date</th>
<th>Number of BSMs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Truck 1</td>
<td>All road sections registered by DSRC</td>
<td>Jul 3, 2015 15:03:45.189162000</td>
<td>Nov 3, 2015 19:47:24.243018000</td>
<td>4,749,912</td>
</tr>
<tr>
<td></td>
<td>Anomalies on selected road</td>
<td>Jul 15, 2015 16:40:15.195829000</td>
<td>Oct 27, 2015 08:44:00.326029000</td>
<td>42,342 (5.95%)</td>
</tr>
<tr>
<td></td>
<td>Anomalies on Mt. Ousley</td>
<td>Oct 27, 2015 08:40:38.025210000</td>
<td>Oct 27, 2015 08:44:00.326029000</td>
<td>2,024 (1.0829%)</td>
</tr>
<tr>
<td></td>
<td>Anomalies on selected road</td>
<td>Aug 23, 2015 07:04:38.270970000</td>
<td>Nov 2, 2015 03:31:06.089445000</td>
<td>2,853,832</td>
</tr>
<tr>
<td></td>
<td>Anomalies on Mt. Ousley</td>
<td>Aug 24, 2015 15:35:39.695137000</td>
<td>Oct 7, 2015 06:13:05.025705000</td>
<td>450 (0.49%)</td>
</tr>
<tr>
<td>Truck 4</td>
<td>All road sections registered by DSRC</td>
<td>Aug 23, 2015 07:04:38.270970000</td>
<td>Oct 23, 2015 03:31:06.089445000</td>
<td>2,766,201</td>
</tr>
<tr>
<td></td>
<td>Mt. Ousley road section</td>
<td>Aug 24, 2015 15:35:39.695137000</td>
<td>Oct 7, 2015 06:13:05.025705000</td>
<td>450 (0.49%)</td>
</tr>
<tr>
<td></td>
<td>Anomalies on Mt. Ousley</td>
<td>Aug 24, 2015 15:35:39.695137000</td>
<td>Oct 7, 2015 06:13:05.025705000</td>
<td>450 (0.49%)</td>
</tr>
<tr>
<td></td>
<td>Anomalies on selected road</td>
<td>Aug 23, 2015 15:35:39.695137000</td>
<td>Oct 26, 2015 15:13:58.525482000</td>
<td>2093 (0.6%)</td>
</tr>
<tr>
<td></td>
<td>Anomalies on Mt. Ousley</td>
<td>Sep 27, 2015 01:15:24.979748000</td>
<td>Sep 27, 2015 01:16:36.743136000</td>
<td>720 (0.69%)</td>
</tr>
</tbody>
</table>
FIGURE 4 Noise mapping and noise distribution for Truck 1, 2 and 3.
Figure 4 shows the noise mapping and noise distribution on the selected road section for the first 3 trucks. We can therefore identify which road areas are susceptible to registering deviations from the road center, which we will define as “noise-prone” areas. Figures 4 a1), b1) and c1) show that the north part of the road is more sensitive to noise, which is near the coal mine where the trucks stop for loading. As well, we can notice that, although Truck 2 registered the biggest number of anomalies, Truck 3 seems to present a large spread in the positioning where the noise is registered.

The noise distribution plot (Figure 4 a2), b2), c2)) confirms again a particular behavior for Truck 3 and 2, as the maximal noise can reach 17.0785 meters in certain locations. In terms of average noise on Mt. Ousley, we make the observation that Truck 5 (not represented here) has the lowest noise levels (2.24 meters average noise from road center), which falls into good levels of positioning on the streets. In furthering the understanding of GPS and BSM accuracy, we suggest these noise-prone locations would be good places to investigate in detail in order to understand the phenomena of common localized issues.

By taking into consideration the global positioning of all the trucks we investigated in CITI, we can state that the average noise obtained for almost all trucks fall under 3 meters, which indicates that the GPS location being transmitted has good accuracy in most of the BSMs. Knowing that the width of a single lane in Australia is about 3.5 meters, and that the road section we have investigated has in general 2 lanes (in smaller portions 3 lanes), then the accuracy of the DSRC positioning is of almost one lane. This finding gives confidence that, overall, the transmitted GPS location of connected heavy vehicles is accurate and could be used for further understanding why collision alerts are failing. Nevertheless, bad positioning accuracy can lead to false alert generation and hinder road safety, especially when trucks are fully loaded with 82 tons of coal. Receiving a false collision alert when trucks are approaching signalized intersection may induce a sudden braking behavior which would reduce road safety and increase the chances of road collisions. This aspect is not to be neglected and further studies need to be undertaken in order to understand the cause of bad positioning accuracy, possibly including: bad placement of antennas, road geometry, speed, heading etc.

4.3 Regression models for noise analysis

In this section we perform a closer investigation of explanatory factors that can influence DSRC GPS noise. Besides GPS observations with longitude and latitude from transmitted BSMs, we also record the following features (variables): Elevation, Speed, Heading, Brakes, Acceleration Longitude, and Acceleration Latitude, in matrix $X_t = [X_{ij}]_{i=1..8,j=1..N_d^{GPS}}$. We also consider the corresponding noise vector $N_t = [N_i]_{i=1..N_d^{GPS}}$ for this time. We then consider the regression problem of predicting $N_t$ from $X_t$, so as to determine the highly predictive features which influence GPS noise.

To avoid the statistical issue of overfitting (28), we separate our data into a training and a testing set. The training set comprised the first 80% of all GPS readings, with the rest falling into the testing set. We then fit a regression model (to be described subsequently) on the training set, and evaluate model performance on the testing set. Performance is evaluated using the mean squared error (MSE). As a baseline, we used the trivial model which predicts the mean of the GPS noise in the training set; any model that performs worse than this is practically useless.

We use two underlying regression models. The first is a decision tree (specifically, one using the
CART algorithm (29)). This model was chosen because it is intuitive to explain, and can easily fit nonlinear relationships in the data. The latter point is especially important in our application: while several other nonlinear methods could be applied, such as kernel support vector machines or neural networks, these usually lack interpretability. At a high level, a decision tree involves making a number of splits of the data based on some thresholding of the feature values. Depending on the outcome of this thresholding, one then fits a sub-model, which is recursively another decision tree. Finally, one terminates at a leaf node, where a hard prediction is made for the target value. This is typically done by the average of the points that fall into that leaf node.

![Decision Tree Diagram]

**FIGURE 5 Outputs of decision tree methods:** a) Decision tree with a fixed depth of 3 levels for $X_t$, b) Features influencing DSRC GPS positioning accuracy.

We fit a decision tree with a fixed depth of 3 levels to the entire training set of GPS readings. The choice of depth was made with interpretability in mind: with greater depth, it is harder to intuitively decipher the final decision rule made by the tree. Further, with a depth of 3 levels, we found this model to give an MSE of 2.4261, which is a nearly 60% improvement over the baseline MSE of...
The output of the tree is shown in Figure 5a), and seems to be intuitive. We find that the most predictive features are the Speed, Elevation, and Heading. The model is seen to separately treat the cases of very low speed (< 11 km/h). For higher speed, the Longitude is seen to be predictive. While this may seem counterintuitive, in fact the longitude indicates high variations in the movement of the truck along the selected road section, as represented in Figure 4a1). We note that owing to the use of thresholding to split the data, it is standard for the result of a decision tree training procedure to be a binary tree. One can post-process the tree to attempt to create more complicated structures, but we did not explore this in the present work.

To further assess feature importance, we fit a gradient boosted decision tree (GBDT) model (30). This is an example of an ensemble method (one that computes a number of individual sub-models, and then considers an appropriately weighted average of them). Such an averaging procedure lends these methods a robustness against overfitting to spurious signals in the data.

We fit a GBDT comprising 500 individual sub-models, to a maximum depth of 2 levels. We found this model to give an MSE of 2.2696, which is a further 6% improvement over the single decision tree model. Compared to a decision tree, it is harder to directly visualize the output of a GBDT, since it comprises hundreds of sub-models. Nonetheless, we can still estimate the overall importance of individual features. We find that the most predictive features that can influence DSRC GPS accuracy are: speed, elevation and heading (Figure 5b), which is largely consistent with the finding from the single decision tree. These results also validate our previous finding of noise evolution on Mt. Ousley which has restricted low speed (40 km/h) for trucks descending the mountain and no overtake option. On Mt. Ousley, the average noise was around 2.3 meters. Knowing that the lane width in Australia is 3.5 meters, this aspect confirmed that all drivers use the left lane and do not overtake. Results indicate that travelling at lower speed on Mt. Ousley provides better positioning accuracy than other road sections with no speed restrictions. On the other hand, investigations regarding the positioning accuracy when heavy vehicles are stopped in parking areas or at red traffic lights indicate a significant jitter between the positions transmitted by consecutive BSMs. This aspects raise future questions in understanding how much exactly is speed affecting the positioning of connected cars and under what circumstances? Elevation and heading are also important factors affecting the GPS locations, as currently the installed DSRC systems has difficulties evaluating when 2 connected trucks are travelling at various heights (ex: one on a bridge, the other under) and therefore the collision alerts should not be generated. The fact that these features are also useful for the GBDT gives confidence that there is a statistically meaningful relationship between these variables and the DSRC GPS noise.

5. CONCLUSIONS

In this paper we conducted a detailed investigation for analysing the GPS positioning accuracy as transmitted in BSMs by heavy vehicles equipped with aftermarket DSRC units, operating in the CITI project. After choosing GSM as main ground truth for noise computation, we showcase the DSRC transmitted positioning accuracy of the 5 most active trucks of CITI fleet, and identify the noise-prone areas in which DSRC false generated alerts can be triggered. Lastly, by conducting a regression analysis method based on gradient boost decision trees we found that (for our data set) speed, elevation and heading were the most predictive of GPS positioning error.

This work is an intial step in the positioning accuracy and accident alerts investigation for
improving road safety. CITI project is an ongoing project, with aims to investigate DSRC use at signalised intersections, as well as improving road safety especially in high concern public areas (schools, kindergardens, etc.). As the DSRC systems are applied more widely, there is a real need for testing and investigating the technology on more light vehicles, in order to improve road safety. Ongoing work is also focusing on the quality of the GPS positioning on a a small number of vehicles which are currently being equipped with both GPS and GLONASS for improving the location detection. As well, a possible perspective would be to conclude on a survey of different GPS receivers with a robust algorithm to reject anomalies.

ACRONYMS

DSRC – Dedicated Short Range Communications
BSM – Basic Safety Messages
GSM – Google Street Map
OSM – Open Street Map
V2V – Vehicle to Vehicle
V2I – Vehicle to Infrastructure
CV – Connected Vehicles
GNSS – Global Navigation Satellite System
GPS – Global Positioning System
RSE – Road Side Units
VANET – Vehicular Ad Hoc Networks
CP – Cooperative positioning
CITI – Cooperative Intelligent Transport Network Initiative
TFNSW – Transport for New South Wales
CITS – Cooperative Intelligent Transport Systems
FCW – Forward Collision Warning
ICW – Intersection Collision Warning
EBLW – Electronic Brake Light
MM – Map Matching Algorithm
MSE – Mean Squared Error
BGDT – Gradient Boosted Decision Tree

REFERENCES


