What is the area of influence of a vehicle on the road? Theoretical Aspects and Some empirical Findings

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Περίληψη

Σε ένα περιβάλλον συνεργατικών οχημάτων, κάθε όχημα (αποστολέας) ανταλλάσσει μηνύματα με τα γειτονικά του (παραλήπτες) εντός του εύρους μετάδοσης του ασύρματου (κυκλοφοριακού) δικτύου. Η περιοχή που περιλαμβάνει όλα τα οχήματα, που αλληλοεπιδρούν μεταξύ τους, ονομάζεται περιοχή επιρροής του αποστολέα. Στόχος της παρούσας εργασίας είναι η εκτίμηση της περιοχής επιρροής χρησιμοποιώντας τις αρχές της θεωρίας της πληροφόρησης και δεδομένα υψηλής ευκρίνειας από μη επανδρωμένα αεροσκάφη. Για το σκοπό αυτό, υπολογίστηκε η αμοιβαία πληροφόρηση μεταξύ δύο οχημάτων, λαμβάνοντας τις ταχύτητές τους ως τυχαίες μεταβλητές. Για τέσσερις χρονικές περιόδους υπολογίστηκε ο μέσος όρος της αμοιβαίας πληροφόρησης του εξεταζόμενου οχήματος με τους γείτονές του για 20 διαφορετικές ακτίνες. Η ακτίνα για την οποία ο μέσος όρος της αμοιβαίας πληροφόρησης του εξεταζόμενου οχήματος με τα γειτονικά παρουσιάζει την ελάχιστη τιμή, θεωρείται κρίσιμη. Βάσει των αποτελεσμάτων, στις περισσότερες περιπτώσεις, η πυκνότητα του οδικού δικτύου αποτελεί καθοριστικό παράγοντα για την αξιόπιστη εκτίμηση της περιοχής επιρροής του οχήματος.

Λέξεις κλειδιά: *Συνεργατικά οχήματα, περιοχή επιρροής, αμοιβαία πληροφόρηση, δεδομένα υψηλής ευκρίνειας, πυκνότητα οδικού δικτύου, ταχύτητα.*

Abstract

Under the Cooperative Vehicles environment, each vehicle (sender) exchanges messages with its surrounding vehicles (receivers) within the transmission range of the wireless (vehicular) network. The area including all vehicles influencing each other is called influence area of the sender. The aim of this work is to estimate the influence area of vehicles using the principles of information theory and high-definition data collected via drones. For this purpose, we computed the mutual information between pairs of vehicles, considering their velocities as random variables. For four time periods the average mutual information between the ego-vehicle and its neighbors is computed for 20 different radius values. The radius that corresponds to the minimum of the average mutual information between the vehicle and its neighbors is considered critical. The results indicate that, in most cases, road density is a critical factor for the reliable estimation of the vehicle's area of influence.

Keywords: *cooperative vehicles, area of influence, mutual information, high-definition data, road density, speed.*

1. Introduction

Vehicle-to-vehicle (V2V) communication is one of the Intelligent Transportation Systems (ITS) technologies aiming to increase road safety and improve human driving experience and behavior. Cooperation and connectivity among vehicles are based on the efficient transmission of information related to their kinematic characteristics, traffic conditions or incident occurrence (European Commission, 2019). In the roads of the near future, each vehicle (sender) will exchange messages with its surrounding vehicles (receivers) within the transmission range of the wireless (vehicular) network. Within this range, the position and kinematic characteristics (e.g speed) of the vehicles determine how their behavior needs to be adapted based on the information received. The area around the sender inside of which all vehicles influence each other is the area of influence of the sender (ego – vehicle) and it refers to the spatial demarcation of its external environment.

Despite the fact that both the wireless vehicular communication and the mutual information (MI) are widely studied, limited research has been carried out combining these two areas. The existing literature on the wireless vehicular communication range reflects a maximum range of 300 m for Vehicular Networks (VANETs) (Yu et al., 2007, Torrent-Moreno, 2007, Jiang et al., 2008) which is consistent with experimental measurements of dedicated short-range communications (DSRC) performed to date (Kukshya et al., 2006, Cheng et al., 2007, Bai et al., 2010, Benin et al., 2012). In these studies, it is noted that communications in urban environments normally involve a range of approximately 140 m., while those in non-urban environments achieve a range of approximately 300 m. It is for this reason that the majority of the studies consider the range of the wireless communication network as a fixed number from 140m to 300m. Wang and Chou (2009) presented NCTUns (EstiNet Network Simulator and Emulator), an open-source integrated simulation platform for wireless vehicular communication network that assumed a transmission range of 250m. Hawas, Napeñas, and Hamdouch (2009) developed and compared two intervehicular communication (IVC)-based algorithms for real time route guidance in urban networks. They tested these algorithms for various communication ranges (radii) for the IVC-forward algorithm; namely, 300, 600 and 900m and concluded that the communication range has a noticeable influence on the frequency of knowledge sharing; the higher the communication range, the higher the likelihood of exchanging knowledge among the searcher vehicle and the candidate vehicles. Moreover, a research report from The United States Department of Transportation on the readiness for application of V2V communications revealed that the ego-vehicle receives messages from the other vehicles in a curvature of 300m radius, assuming that all vehicles are equipped with V2V technology (Harding et al, 2014). Liu et al (2016) proposed a network-coding-assisted scheduling algorithm to enable the hybrid of V2V and vehicle-to-infrastructure (V2I) communications and exploit their joint effects on providing efficient data services. In the case of V2V, the communication radius of the roadside units (RSU) is set to 600m, and the V2V communication range is set to 300m.

Apart from a few studies in the field of transportation engineering, information theory has not been extensively applied so far. For instance, Kaza et al. (2005) use the MI concept to identify vehicles that frequently cross the border with vehicles that are involved in criminal activity. However, most papers that apply the principles of information theory or any other theory of machine learning mainly focus on the short-term traffic flow prediction (Vlahogianni et al, 2007, 2008, 2009, Ryu et al, 2018).

To our knowledge, the radius of a conventional vehicle's area of influence has not been yet explored. Additionally, regarding the range of a wireless communication network further research needs to be done. Within this context, this study addresses the need to compute the range of a vehicular network, not by assuming it as a fixed number, but through the estimation of the area of influence of a conventional vehicle based on real time driving data. Specifically, we aim to develop a methodology to estimate the area of influence of conventional vehicles under different traffic conditions and for various vehicle types based on principles of information theory and detailed human driving vehicle trajectory data. The remainder of the paper is as follows: the next section presents the methodological approach. Following, the implementation specifications are presented and the results are discussed. Finally, the paper ends with the conclusions section with a discussion on some future research directions.

2. Methodological Approach

2.1 Problem Setup

The term "area of influence" refers to the spatial demarcation of the external environment of the ego vehicle. We assume that it is a circle centered at the ego-vehicle and includes all the neighboring vehicles, that interact with the sender. It is important to note that the area of influence of a conventional vehicle is not identical to the transmission range of an autonomous vehicle. The difference eagers to the fact that the latter is bigger than the former, in order to ensure the transmission of the message to the affected surrounding vehicles.

In this research, the area of influence is defined based on conventional vehicles' trajectory data collected in the center of Athens during morning peak hours (pNEUMA dataset) via Unmanned Aerial Systems (UAS), the so called "drones" (Barmpounakis et al, 2020). To estimate the area of influence, we compute the mutual information (MI) between pairs of vehicles (sender-receiver), considering their velocities as random variables. This will reveal the identification of any effect the speed of the first vehicle might have on the second one and vice versa. By computing the mean of the MI that each ego-vehicle shares with its neighboring vehicles for different radius values, the critical radius of the influence area can be derived. We analyze the results based on the vehicle type and the road density and the goal is to adapt the results to future researches focusing on autonomous vehicles.

2.2 Basic Principles of Information Theory

Entropy or Shannon Entropy, as it called after its founder Claude Shannon (1948), is a measure that reveals the amount of uncertainty contained in the outcome of the value of a random variable or the result of an experiment. Let X be a random variable with probability distribution function p (x). Then, the entropy of the random variable X is defined as:

$$H(X) = -\sum_{i=1}^{n} P(x_i) log_b P(x_i) \quad \textbf{(1)}$$

where b is the base of the algorithm and determines the units in which the information is measured. More precisely, base 2 leads to information measured in bits, whereas base e leads to information measured in nats. In the present work, we use natural algorithms.

MI is a measure of independence between random variables, that has singled out due to its information theoretic background originating from its close ties to Shannon entropy. Estimating

MI is not an easy task when it comes to continuous variables. Two are the most straightforward and widespread approaches for computing this measure. The first estimator is based on partitioning the supports of X and Y into bins of finite size and is obtained by counting the numbers of points into the bins. The MI is then

$$I(X;Y) \approx \mathrm{I}_{binned}(X;Y) = \sum_{i,j} Pxy(i,j) log \frac{Pxy(i,j)}{Px(i)Py(j)} \quad \textbf{(2)}$$

In Eq.2 if $n_x(i), n_y(j)$ and $n(i,j)$ the number of points falling into the i[th] bin of X, j[th] bin of Y and in their intersection respectively, then $Px(i) \approx n_x(i)/N$, $Py(j) \approx n_y(j)/N$, $Pxy(i,j) \approx n(i,j)/N$.

The second estimator was proposed by Kraskov (2004), it is considered to be accurate and reliable and is the one that we implement in this paper. The method uses the k-nearest-neighbors (knn) algorithm and has the following form (Eq. 3):

$$I(X;Y) = \psi(k) - \langle \psi(n_x+1) + \psi\big(n_y+1\big) \rangle + \psi(N) \quad \textbf{(3)}$$

where

$\psi(k)$ is the digamma function.

$n_x(i)$ is the number of points x_j whose distance from x_i is less than $e(i)/2$ (the distance from z_i to its kth neighbor), similarly for y.

3. Implementation

3.1 Data

The data used for this study are obtained through a first-of-its-kind experiment, named pNEUMA, that was conducted in the center of Athens during morning hours. More precisely, Unmanned Aerial Systems (UAS) or simply “drones” recorded the road conditions in ten sites in order to create a complete urban dataset (Barmpounakis et al, 2020). In the context of this study, the analyzed data are collected from a single site, on Alexandra’s Avenue from 09:30am to 10:00am. The dataset includes the id, coordinates, speed, acceleration, deceleration and the type of the vehicle for all vehicles of the road monitored for 1229 timepoints of 0.8 seconds each.

In order to measure the independence of two random variables using MI, we need a sufficient amount of data. Therefore, we analyze only the vehicles that appeared on the road for at least 52 timepoints, i.e. 41.6 seconds. As a result, the final dataset consisted of 387 vehicles and had the following form (Table 1).

***Table 1:** Dataset.*

Vehicle I.d.	Vehicle Type	X coordinate	Y coordinate	Speed	Longitudi-nal Acc.	Lateral Acc.	Time
63	4.00000	2890133.79511	2040849.54281	30.79690	-0.20700	0.11080	1600.00000
64	2.00000	2890133.78080	2040919.92222	11.34350	-0.17740	-0.02060	1600.00000
65	6.00000	2890128.47145	2040992.11787	0.00000	0.00000	0.00000	1600.00000
66	1.00000	2890129.73483	2040997.85672	5.02250	-0.34840	-0.00060	1600.00000
67	5.00000	2890129.93406	2041021.98358	17.83100	0.01960	1.77190	1600.00000

The second column of the dataset refers to the vehicle type and takes values from 1 to 6, each value presenting a different vehicle type. More precisely, type number 1 stands for the power-two wheelers (ptws), number 2 for the private passenger cars, number 3 for the taxis, number 4 for the vans, number 5 for the trucks and number 6 for the buses. When a vehicle appears on the examined road section, the coordinates X and Y take values other of zero. The y-y' axis coincides with the axis of the road, whilst x-x' is the perpendicular axis as seen in Fig. 1.

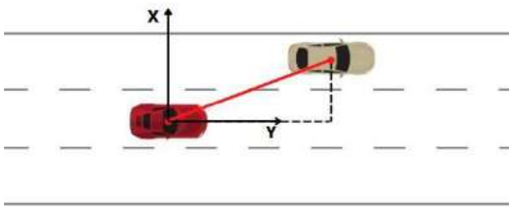

***Figure 1:** Distance between vehicles.*

3.2 Defining the neighboring vehicles

Each vehicle was analyzed for four consecutive time periods, 10.4 seconds each, in order to have at least 10 dataset points for the reliable estimation of MI. The first period of each vehicle refers to its first 13 dataset points for which the ego-vehicle was on the road, the second period refers to the next 13 dataset points etc.

For each vehicle and each time period, we compute the information that the ego-vehicle shares individually with all the vehicles within a specified range of radius R. The number of the neighboring vehicles varies depending on the examining radius of the area of influence. In particular, 20 different radius values between 10-200m. are analyzed, with a step of 10m. A vehicle is considered as a neighbor of the ego-vehicle if the distance $Dist_{i,j}$ between them is less or equal with the examining range of communication. We denote as $Dist_{i,j}$ the Euclidian distance between vehicles i and j as following.

$$Dist_{i,j} = \sqrt{\left(x_j - x_i\right)^2 + \left(y_j - y_i\right)^2} \tag{4}$$

In Eq.4, x and y refer to the coordinates of each vehicle, which are considered to relate to their center (Fig.1). As critical radius of the area of influence of each vehicle for the under-investigation time period is considered the one for which the average MI of the ego-vehicle with its neighbors reaches its minimum value.

The results are further analyzed based on the vehicle type and the road density as shown below.

3.3 Results

The following figures display the results after the analysis of each vehicle. (Fig. 2, 3, 4). Figure 2 demonstrates the neighbors of a specific vehicle (car 62) for its first time period.

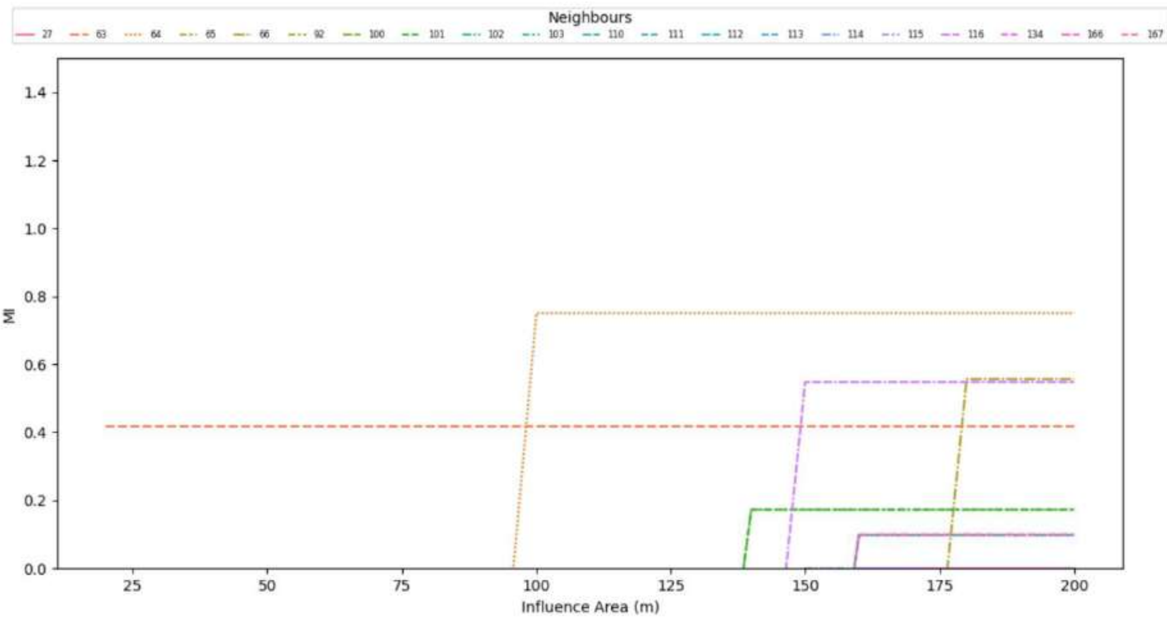

Figure 2: *Neighbors line plot for car 62 at first time period.*

At the top of Figure 2 the ids of the neighbors are demonstrated. We observe that by increasing the radius the list of neighbors is gradually expanded to include the farthest vehicles as well. The MI between the subject vehicle and its neighbor remains constant throughout the whole period. It can also be observed that there are neighbors' ids that do not correspond to any line in the plot. In this case, despite the fact that the neighbor is within the range, the information shared with the ego-vehicle is zero.

The next graph shows briefly the range of MI values between car 62 and its neighbors for every examining radius in its first period.

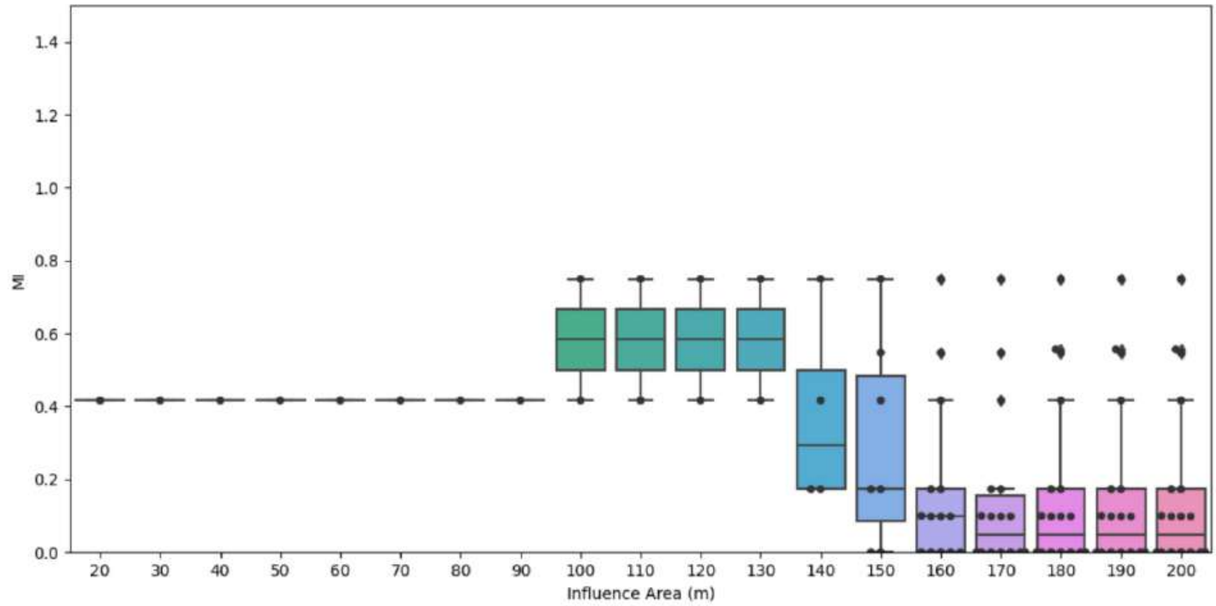

Figure 3: *Neighbors box plot for car 62 at first time period.*

In figure 3 the black dots are the MI values of the ego-vehicle with its neighbors while the the dash symbolizes the median of the MI for each radius. Compared to Figure 2, the neighbors, that share zero information with car 62, are depicted. Figure 4 displays the average MI between the ego-vehicle and its neighbors with respect to the radius for a specific time period.

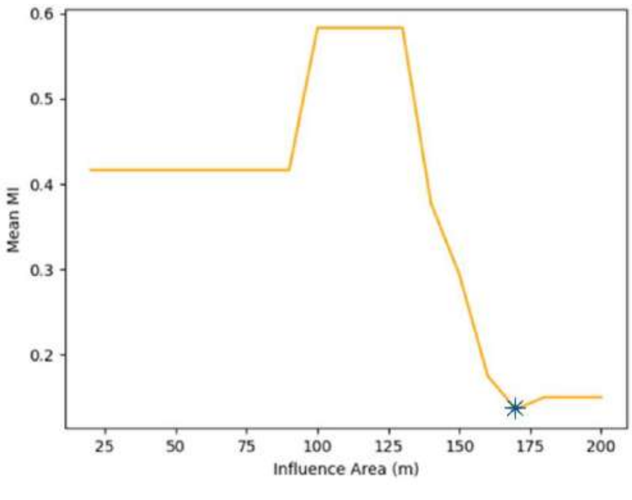

Figure 4: *Mean MI for every radius value for car 62,1st period.*

In Figure 4 the asterisk symbolizes the minimum value of the average MI between car 62 and its neighbors and therefore the critical radius of the influence area is equal to 170m for car 62 for its first period.

It is worth mentioning that in some cases, for low radii the ego-vehicle did not show a stable neighbor during the analyzed period. For this reason, in such cases the lowest value for which the MI is plotted is above 10 meters as shown in figure 4. The upper value of MI was in rare cases higher than 1.5.

Thus, the results with respect to the vehicle type and road density are presented in a final table part of which is displayed in Table 2.

***Table 2:** Part of the analysis results.*

Time Period	Vehicle I.d.	Vehicle Type	Road Density (v/km)	Influence area (m)
1	27	1	60	10
1	44	2	15	150
1	45	2	10	30
1	48	2	20	50
1	54	2	20	200
1	62	2	10	170
1	63	2	10	160
1	64	2	70	80
1	65	5	60	30
1	66	1	60	30
1	84	2	10	140
1	87	2	5	130
1	88	2	10	180
1	92	1	25	200
1	99	2	10	50
1	100	2	25	200
1	103	2	25	170
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.

Extending the findings of Table 1, Figures 5 and 6 illustrate how the density of the road section influences the range of communication for each vehicle type. We also present the logarithmic or exponential equations that best describe the results accompanied by the corresponding coefficient of determination R^2 (Fig. 5-7). The coefficient R^2 takes values from 0 to 1. Values close to 1 indicate a perfect fit of the model to the data. As seen in Fig. 5-7, private passenger cars have a coefficient of determination close to 0.70, taxis and power-two wheelers present R^2 of almost 0.45 and 0.50 respectively while trucks and buses have low coefficients, close to zero. The vans also show a satisfactory coefficient of determination of 0.65. In addition, the logarithmic lines of cars and taxis are almost identical to each other, as is their cumulative logarithm with that of all vehicles. The resulting equation of private passenger cars when studied along with taxis shows R^2 close to 0.65 and the resulting equation of all vehicle types, when studied as whole, describes the results in the 0.70 of the cases. Lastly, the exponential trend line of vans and trucks cumulatively has a coefficient of determination close to 0.45.

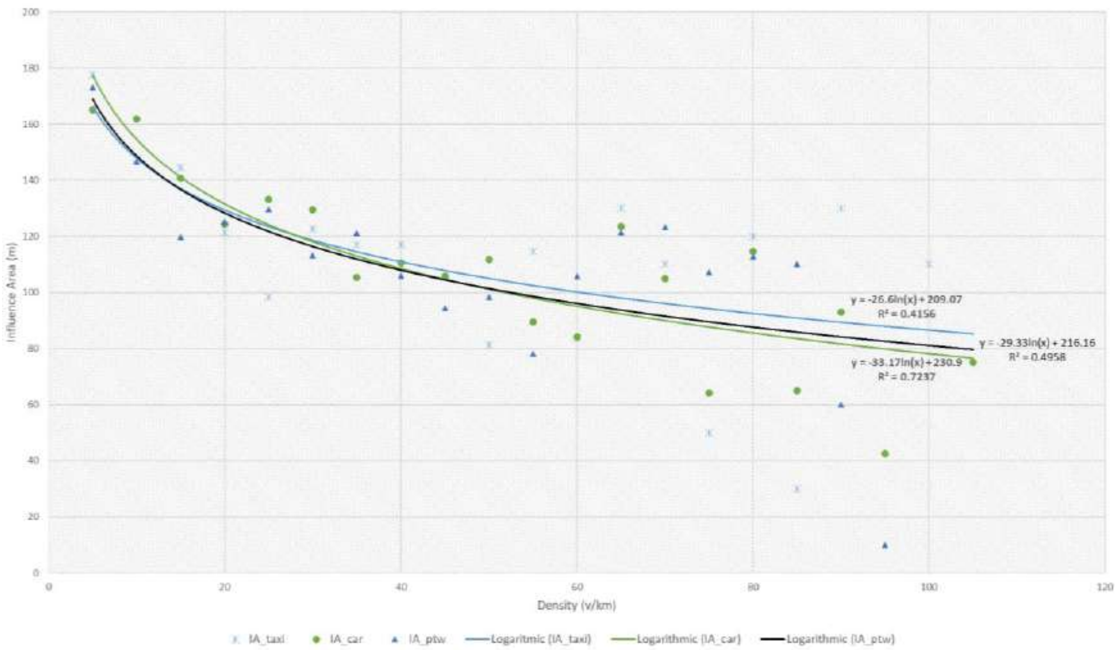

Figure 5: *Logarithmic equations of power-two wheelers, cars and taxis.*

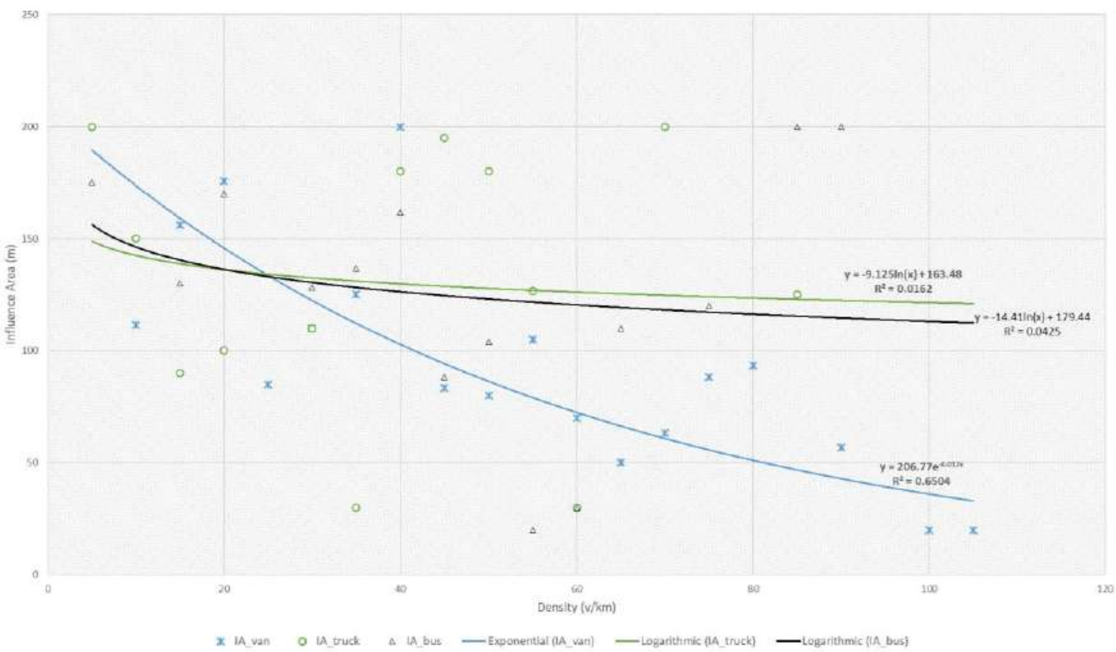

Figure 6: *Logarithmic and exponential equations of trucks, buses and vans.*

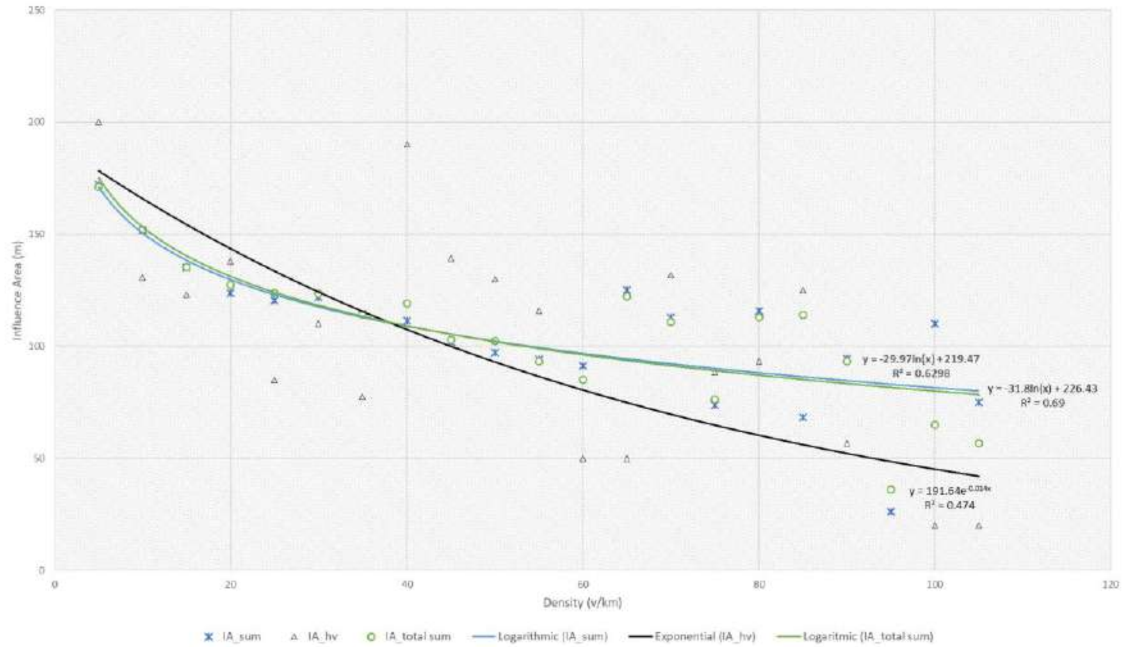

Figure 7: *Logarithmic and exponential equations of vehicles' sets.*

Concerning the powered-two wheelers, the private passenger cars, the taxis and the vans respectively, there is a downward trend, meaning that a potential decrease of the critical radius of the influence area follows a concurrent increase of the road density. On the other hand, for the trucks and buses respectively, the pattern is not that clear.

By visualizing the impact of the road's density on the dimension of the critical area of influence we notice that in some occasions, while the density is high, the radius of the influence area is equally large, reaching even 200 meters. This means that the ego-vehicle shared almost the same speed with many neighboring vehicles on the road network and as a result no minimum value was detected. Such cases usually appear in an analysis using only speed as a variable, as two vehicles can have similar speeds regardless of their interdependence. Besides this randomness, though, the initial limitation of the data may also be an important factor. Some vehicles that appeared on the road network and affected the ego-vehicle, may not have been analyzed due to their time-limited presence.

Regarding the power-two wheelers, the private passenger cars and the taxis, road density is an important determinant for the reliable estimation of the area of influence of the vehicles; the lower the density, the larger the radius of influence of the vehicle and vice versa. In cases of traffic congestion, the driver usually tends to observe the vehicles closest to him. On the other hand, the influence area of trucks and busses seems to be slightly related to the prevailing road density conditions. This conclusion needs further investigation, as it not clear whether it occurs due to their particular way of moving in the network or due to the small number of similar vehicle type studied. Regarding the vans the results indicated that, at least in terms of road density, they develop behavior similar to that of the private passenger cars.

4. Conclusions

In this work, we estimated the area of influence of different vehicle types by computing the MI between pairs of vehicles. Using the speed as the random variable we concluded that it is capable of providing reliable results concerning the estimation of the influence area of a vehicle. By further analyzing the results we tried to develop a relationship between the area of influence of a vehicle, the vehicle type and the road density and observed that road density is an important factor in determining the radius of influence when all vehicle types are studied as a whole. However, by studying each type separately, buses and trucks seem to be slightly depended on the density of the network. In addition, we proposed the logarithmic and exponential equations and noted that they better describe the results of the power-two wheelers, the private passenger cars and the vans. The high percentage of the coefficient of determination of private passenger cars along with the taxis leads us to the conclusion that the results presented in this paper are reliable for all vehicle types except for the trucks and the buses.

Future work could focus on evaluating the use of different traffic parameters as metrics for the estimation of the critical area. The results presented in this paper can be also analyzed based on other factors, such as the driver's behavior and contrast the range of influence of aggressive drivers compared to conservative ones. Finally, the proposed approach can be used to produce control strategies for both manually driven and autonomous vehicles and assess their impacts to traffic and safety at different network scales in a simulation environment.

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