A Framework to Assess Value of Information in Future Vehicular Networks

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ABSTRACT

Vehicles are becoming increasingly intelligent and connected, incorporating more and more sensors to support safer and more efficient driving. The large volume of data generated by such sensors, however, will likely saturate the capacity of vehicular communication technologies, making it challenging to guarantee the required quality of service. In this perspective, it is essential to assess the *value of information (VoI)* provided by each data source, to prioritize the transmissions that have the greatest importance for the target applications. In this paper, we propose and evaluate a framework that uses analytic hierarchy multicriteria decision processes to predict VoI based on space, time, and quality attributes. Our results shed light on the impact of the propagation scenario, the sensor resolution, the type of observation, and the communication distance on the value assessment performance. In particular, we show that VoI evolves at different rates as a function of the target application's characteristics.

CCS CONCEPTS

•**Computer systems organization** →**Embedded systems;** *Redundancy;* Robotics; •**Networks** →Network reliability;

KEYWORDS

Vehicular networking (V2X); value of information (VoI); analytic hierarchy process (AHP)

1 INTRODUCTION

The automotive industry is evolving towards Cooperative and Intelligent Transportation Systems (C-ITSs) to support advanced applications ranging from improved safety to infotainment [18]. Intelligent vehicles will be equipped with sophisticated sensors, including radars, cameras and LIDARs, whose data rate requirements (in the order of terabytes per driving hour [12]) may exceed the capabilities of existing vehicular communication technologies.

In this scenario, new communication radios operating in the millimeter wave (mmWave) bands above 30 GHz have been investigated because of the large bandwidth available at high frequencies [5, 7]. Mobile edge computing [13] and vehicle cloudification [8] have also emerged as promising solutions to meet strict delay requirements leveraging computation resources at the edge of the network and virtual cloud computing facilities formed by vehicles' on-board computers, respectively.

In this context, it is fundamental to set a bound on the amount of information that is distributed over bandwidth-constrained communication channels. A traditional approach is to monitor the *age of information (AoI)* [11], i.e., the obsolescence of the data, so that vehicles broadcast sensory messages that are not too old. However, the complex dynamics of vehicular networks affect the rate of decay of the information, making it difficult to set a fixed threshold for the AoI to discriminate between useful and obsolete pieces of data. Another approach is to discriminate the *value of information (VoI)* [9, 14] in order to use the (limited) transmission resources in a way that maximizes the utility for the target applications.

The VoI theory has originally been applied to the military context to prioritize the information to be distributed to soldiers in a battlefield environment [20], although such strategies do not account for cases where the information sources are not directly under the users' control. VoI has also been investigated in underwater systems [4] and Internet of Things (IoT) applications [3] to decide how much information to transmit through resource-constrained channels. However, while IoT sensors are mostly static and operate in steady conditions, connected cars are expected to move very rapidly, thereby posing new challenges for proper VoI characterization.

In this paper, we investigate for the first time the concept of VoI in vehicular networks. We therefore propose a method to assess VoI and rank scheduling options as a function of the characteristics of the network in which the nodes are deployed. Traditionally, VoI assessment strategies, even though not in the vehicular context, try to balance transmissions of non-critical information and timely dissemination of high-priority data. Some others, e.g. [2], use machine learning to assign VoI based on the degree of correlation among the information sources, although operations are typically computationally heavy, and they can hardly be completed under low latency constraints. Adaptive approaches, e.g. [10], use feedback to predict VoI, which however incurs non-negligible overhead and communication delays. Along these lines, a more natural (and practical) solution to assign VoI is to define automotive-specific criteria (i.e., attributes) which depend on the receiver's context and application. Our innovative framework, in particular, exploits analytic hierarchy decision processes (AHP) to quantify the expected value of information based on time, space and quality interdependencies. We validate the technical accuracy of this approach in realistic scenarios and show how VoI evolves as a function of the scenario (i.e., urban or highway), the sensor resolution, the type of observation, the communication distance and the age of information. Thanks to its generality and computational simplicity, our

method guarantees timely and efficient value assessment operations. Through our investigation, we also provide guidelines on the optimal network configurations and data scheduling alternatives that intelligently select information to be sent at each transmission opportunity while maximizing the utility to potential receivers.

2 VOI IN VEHICULAR NETWORKS

VoI is extremely context-dependent, i.e., different outcomes are possible depending on the characteristics (and requirements) of the application and the sources of information that are being considered.

Let $\mathcal{V}$ denote the set of vehicles in the scenario which are equipped with on-board sensors (e.g., cameras) and a hardware unit enabling Vehicle-to-Vehicle (V2V) communications. At time t, a vehicle $v_i \in \mathcal{V}$ perceives a road object through its on-board sensors, and generates a perception record $o_i(t)$, i.e., the vector of sensors' measurements, for each of the detected objects. Our key research question in this work is whether vehicle $v_i \in \mathcal{V}$ should broadcast perception record $o_i(t)$ to potential receivers. For example, $o_i(t)$ may not be so valuable if destination nodes are not able to receive the perception message in a timely way. We assess that vehicles should distribute the information about each perceived observation only if its value is above a pre-defined threshold for at least one vehicle within the communication range. Such a threshold, in turn, may depend on the target application.

In this paper, we focus on two broad application domains that, for their generality and complementarity, we believe are good representatives of future vehicular services.

- *Advanced Safety:* It enables semi- or fully-automated driving through dissemination of sensor data, thereby promoting safer traveling and collision avoidance. These applications are typically characterized by strict latency requirements to guarantee real-time operations.
- *Traffic Management:* It enables traffic control and coordination through the creation of a Local Dynamic Map (LDM) [6], which integrates sensor data streamed by vehicles in a geographical area. These operations may require relatively high data rate compared to safety applications, while some latency can be tolerated (depending on the degree of automation).

In the following, we discuss the information sources and the attribute categories that affect VoI.

2.1 Information Sources

As C-ITSs evolve towards the support of safety-critical applications, it is fundamental to implement network architectures that guarantee timely and accurate positioning of vehicles. Positioning is typically provided by the Global Positioning System (GPS) (which also guarantees accurate time synchronization among vehicles), although other localization techniques, e.g., based on image processing, can be useful to improve accuracy. In this paper, we consider camera sensors as the principal information source to enable position estimation. The accuracy of the camera observations depends on (i) the resolution of the sensor, which is a measure of the image width/height and the frame rate, (ii) the field of view, and (iii) the operating distance.

2.2 Vehicular Attributes

VoI typically decays over time at a rate that is application dependent. Value determination should indeed account for specific attributes, e.g., timeliness, spatial proximity and quality, as defined next.

- *Timeliness:* VoI decreases with the relative age of information, i.e., the time between the generation and reception of the information, normalized to its lifetime, i.e., the temporal horizon over which that piece of information is considered valuable.
- *Proximity:* VoI is a function of (i) the distance between the information source and destination, i.e., sensory data generated by close-by vehicles are generally more valuable than data coming from farther nodes, and (ii) the scenario, i.e., urban/highway.
- *Information Quality:* VoI depends on (i) the intrinsic quality of the information source, which may be assessed in terms of sensor resolution, and (ii) the distance between the source sensor and the observation (e.g., the depth measurement error increases proportionally with the distance).

In general, VoI can be also affected by network parameters. We do not preclude in the future to further extend the list of attributes included in this paragraph with other factors including, e.g., the vehicle density, the role of a vehicle in the network (e.g., platoon head, cluster coordinator, etc.), and the road topology.

3 VOI ASSESSMENT FRAMEWORK

In this paper, we consider two possible embodiments of VoI assessment: processed and non-processed approaches. The trade off involves latency, energy consumption and VoI accuracy. In the first case, the perception record is analyzed by the sender to extract context information (e.g., estimated positions of objects in a captured image) before being broadcast. While incurring some processing delays, this allows the sender to validate the integrity of the observation and determine whether it embeds valuable characteristics for the potential receiver(s). In the second case, the perception record is broadcast immediately after it is generated, thereby yielding a more responsive value assessment operation. The sender, however, needs to predict *probabilistically* the value of the observation to prevent circulation of duplicate or redundant data.

The proposed framework performs VoI assessment operations through three main phases, as illustrated in Fig. 1 and described next.

Phase 1: Attribute Priority Weights (via AHP)

First, the algorithm applies the Analytic Hierarchy Process (AHP) to derive the relative degree of priority among the vehicular attributes, i.e., timeliness, proximity and quality, by populating a pairwise comparison matrix M (as illustrated in the left frame of Fig. 1) with comparison scores (i.e., α, β, γ) [15]. The comparison scores in M (ranging from 1/9 to 9) are assigned according to the Saaty comparison scale [17] and assess the importance of the attributes in the row relative to those in the column (e.g., the score 3 is assigned if the item on the row is "moderately more important" than the item on the column in the specified application domain). Note that M is reciprocal by construction, i.e., $M(j, k) = 1/M(k, j)$, $\forall j, k \in \{1, \ldots, n\}$, where n is the size of M, i.e., the number of attributes.

As soon as the comparison scores have been determined, priority weights w_a, $a = 1, \ldots, n$, are computed evaluating the normalized principal eigenvector $\vec{w} = \langle w_1, \ldots, w_n \rangle$ of M, i.e., the eigenvector that corresponds to the eigenvalue $\lambda_{\max}$ with the largest magnitude:

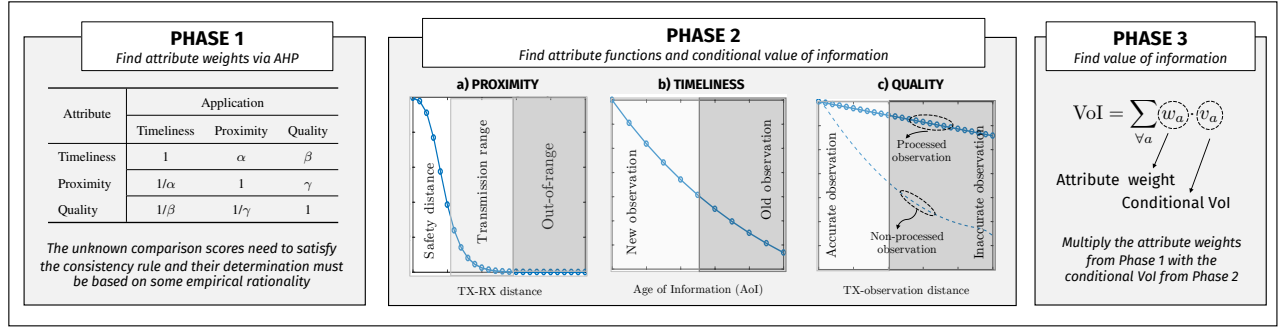$$M\vec{w} = \lambda_{\max}\vec{w}. \tag{1}$$

Fig. 1: Illustrative scheme of VoI assessment framework proposed in Sec. 3.

The priority weights indicate how valuable each attribute is compared to the others. It appears clear that the AHP method determines relative (instead of absolute) priority weights, which are based on empirical evaluation criteria, and consequently have a certain degree of arbitrariness. According to the AHP, in order for the weight vector $\vec{w}$ to be a good representative of the relative importance of the attributes, the matrix M should be consistent, i.e., such that $M(j,k) = M(h,k)/M(h,j), \forall h,j,k \in \{1,\ldots,n\}$. However, given the arbitrariness in the attribute selection, the matrix M is usually not consistent. A measure of the matrix consistency is given in [15] in terms of the so-called *consistency index* $C_I = (\lambda_{\max} - n)/(n-1)$. Based on [15], the weight vector $\vec{w}$ can be considered acceptable if M satisfies the following consistency rule:

$$C_R = \frac{C_I}{R_I(n)} = \frac{(\lambda_{\max} - n)/(n-1)}{R_I(n)} < 0.1, \qquad (2)$$

where R_I is the average of the C_Is obtained by randomly generating reciprocal matrices of size n (for $n = 3$, we get $R_I = 0.58$).

Phase 2: Conditional VoI

The framework is now used to assess how VoI evolves, conditioned to each attribute. Considering the $n = 3$ attributes presented in Sec. 2.2, different VoI functions are defined.

a) Proximity: For the proximity attribute, we propose to use a logistic function to model VoI dependency on the distance d (in meters) between the information source and the destination, as represented in the first box of the middle frame of Fig. 1. The logistic function is always monotonically decreasing in d, but tuning the function's parameters it is possible to move from a smooth and quasi-linear decrease of VoI with d to a step-like behavior, where VoI is almost constant within a certain range from the source and suddenly drops to zero beyond that range. The function is given by:

$$v_1 = A + \frac{K - A}{\left(C + Qe^{-B(d-d_s)}\right)^{1/\nu}}. \qquad (3)$$

Parameters in Eq. (3) are selected so that $v_1 \simeq 1$ as $d \to 0$ and $v_1 \simeq 0$ as $d \to \infty$, i.e., beyond the communication range, and their values will be detailed in Table 1. In particular, d_s is the safety distance (in meters) and determines the threshold beyond which v_1 starts decreasing. d_s is therefore a function of the scenario, i.e., urban/highway, in which the vehicles are deployed.

b) Timeliness: For the timeliness attribute, we propose to use an exponential function [4], as represented in the second box of the

middle frame of Fig. 1, i.e.,

$$v_2 = \exp(-P_{\text{td}} \cdot (t - t_0)), \qquad (4)$$

where $(t - t_0)$ represents the AoI (in seconds), and P_{td} is the temporal decay parameter. In particular, $P_{\text{td}} = 0$ indicates that the information is not delay sensitive, while a large P_{td} models a quick obsolescence of the information.

c) Quality: We propose that VoI for the quality attribute evolves as a function of the distance d_o (in meters) between the source sensor and the perceived observation, as represented in the third box of the middle frame of Fig. 1. We distinguish between processed (p) and non-processed (np) VoI assessment operations. In the processed case, VoI depends only on the characteristics of the sensor [19]. With reference to the camera sensor, we get

$$v_3^p = 1 - \frac{d_o}{h \cdot f_d}, \qquad (5)$$

where h is the height of the sensor, and f_d is the focal distance. In particular, f_d depends on the camera image resolution in the horizontal domain (r_h) and the field of view (f_w) in degrees, so that

$$f_d = \frac{r_h/2}{\tan(f_w/180 \cdot \pi/2)}. \qquad (6)$$

In the non-processed case, the sender does not know the content of the perception record, therefore it has to identify a method to probabilistically predict whether such record embeds valuable information. We assume that a certain observation (e.g., object) can be detected if it is in Line of Sight (LOS) with respect to the sensor's field of view. The LOS probability is a function of d_o and the propagation scenario, and is modeled as in [1]:

$$P_{\text{LOS}}(d_o) = \begin{cases} \min\{1, 1.05e^{-0.0114d_o}\} & \text{if urban} \\ \min\{1, (2.1 \cdot 10^{-6})d_o^2 - 0.002d_o + 1.02\} & \text{if highway} \end{cases} \qquad (7)$$

The conditional VoI is finally computed as

$$v_3^{np} = \left(1 - \frac{d_o}{h \cdot f_d}\right) \cdot P_{\text{LOS}}(d_o). \qquad (8)$$

Phase 3: Overall VoI

Finally, the framework assigns the value of information v by multiplying the attribute weights w_a, $a = 1, \ldots, n$, from Phase 1 with the conditional VoI v_a, $a = 1, \ldots, n$, from Phase 2:

$$v(d, t, d_o) = \sum_{a=1}^{n} w_a \cdot v_a. \qquad (9)$$

Parameter	Value
Sensor height h	1.2 m
Camera Field of view f_w	70 deg
TX/obs distance d_o	$d/2$
TX/RX distance d	$\{1, \ldots, 500\}$ m
Age of information $t - t_0$	$\{0, \ldots, 5\}$ s
Safety distance d_s {urban, highway}	$\{24, 72\}$ m
Temporal decay P_{td} {static, variable, dynamic}	$\{0, 1, 10\}$
Log. function params {A,K,C,Q,B,V}	$\{1, 0, 1, 1, 0.03, 0.2\}$
Camera resolution r_h {low, medium, high}	$\{640, 1280, 4096\}$ px

Table 1: System parameters.

A *data scheduler* finally sorts the information products in descending order of values and sequentially forwards them to the surrounding receivers. The scheduler may also cancel transmissions of information whose value is below a pre-defined threshold θ_v.

4 FRAMEWORK VALIDATION AND RESULTS

In this section we validate the technical soundness of our proposed framework in target use cases. Our results can be used as a basis for evaluating the optimal data scheduling strategy that maximizes the utility of the transmitted information for the final receiver(s).

The system parameters are based on realistic design considerations and are summarized in Table 1. For the proximity attribute, we calculate the safety distance d_s between vehicles as $d_s = 2 \cdot v_{\max}$ [16], where $v_{\max}$ is the speed limit, which we set to 12 m/s and 36 m/s in urban and highway scenarios, respectively. We also let the distance d between the sender and the receiver vary from 1 to 500 m. For the timeliness attribute, we consider static (e.g., fixed road construction), variable (e.g., temporary social/political events), and dynamic (e.g., pedestrian crossing the street) observations, which correspond to $P_{td} = 0, 1, 10$, respectively. We let the AoI parameter $t - t_0$ vary from 0 to 5 s. For the quality attribute, we consider low-, medium- and high-quality sensors, which are modeled as 640×480, 1280×720, and 4096×780 pixel cameras, respectively. The sensor is placed at a distance $h = 1.2$ m from the road surface, and the field of view is set to $f_w = 70$ degrees. We also assume that the target observation is placed at distance $d_o = d/2$ from the camera sensor. We recall that, in order to exemplify the approach, in this work we focus on the evaluation of VoI for the position data provided by cameras.

Phase 1 results – *attribute weights*. In Table 2 we report the pairwise comparison matrices M which assess the interdependencies among the considered VoI attributes.[1] For instance, for safety applications, we chose to set the proximity vs. timeliness score

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[1]Notice that the comparative scores we consider in Table 2 are chosen in such a way that the consistency rule defined in Eq. (2) is satisfied. Other combinations of scores can be also considered, as long as they are selected in a way that guarantees that the

Attribute	Application: Safety			
	Timeliness	Proximity	Quality	Weight $\vec{w}$
Timeliness	1	1/7	1	0.1194
Proximity	7	1	5	0.7471
Quality	1	1/5	1	0.1336

Attribute	Application: Traffic Management			
	Timeliness	Proximity	Quality	Weight $\vec{w}$
Timeliness	1	9	3	0.6554
Proximity	1/9	1	1/7	0.0549
Quality	1/3	7	1	0.2897

Table 2: Pairwise comparison matrices M_a and weights $\vec{w} = \langle w_1, w_2, w_3 \rangle$ of VoI attributes for safety and traffic management applications.

to 7 since we deem extremely important for vehicles to monitor space while broadcasting context information (e.g., vehicles need to know when the neighbors' distance falls below the safety-critical threshold to trigger collision avoidance transmissions and, at the same time, should defer or cancel transmissions relative to spatially far vehicles). For traffic management applications, we decided to set the proximity vs. timeliness score to 1/9 since the broadcasting decision does not have to be space-dependent (i.e., LDM updates should be addressed to both spatially close and far neighbors). Attribute weights $\vec{w} = \langle w_1, w_2, w_3 \rangle$ are determined from Eq. (1) and demonstrate that the dissemination of space-related information is very valuable to safety services ($\max_{\vec{w}} = w_2 = 0.7471$) while, for traffic management services, time-related information should be preferred ($\max_{\vec{w}} = w_1 = 0.6554$).

Phase 2 results – *conditional VoI*. In Fig. 2a we plot the conditional VoI for the proximity attribute as defined by the logistic function in Eq. (3). We can see that the value of position information is generally higher for a highway scenario than for an urban one. This is consistent with the fact that the larger safety distance between vehicles in highway scenarios requires the information to be disseminated over longer ranges, in order to reach the nearby vehicles. Furthermore, the highway scenario is usually characterized by better propagation conditions that increase the probability of successful reception at long distances and, consequently, the value of the packet transmission itself. Accordingly, VoI drops to zero beyond 300 m, which thus represents a suitable communication range for vehicular networks. In Fig. 2b we plot the conditional VoI for the timeliness attribute as follows from the exponential function in Eq. (4), which is proportional to the AoI and the temporal characteristics of the perceived object, as defined in Sec. 2. In particular, the value is constant in case of static observations while, for dynamic observations, it decreases at a pace that is a function of P_{td}.

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assigned attribute interdependencies are fully representative of the characteristics of the application under consideration.

(a) Proximity. (b) Timeliness. (c) Information quality (processed). (d) Information quality (non-processed).
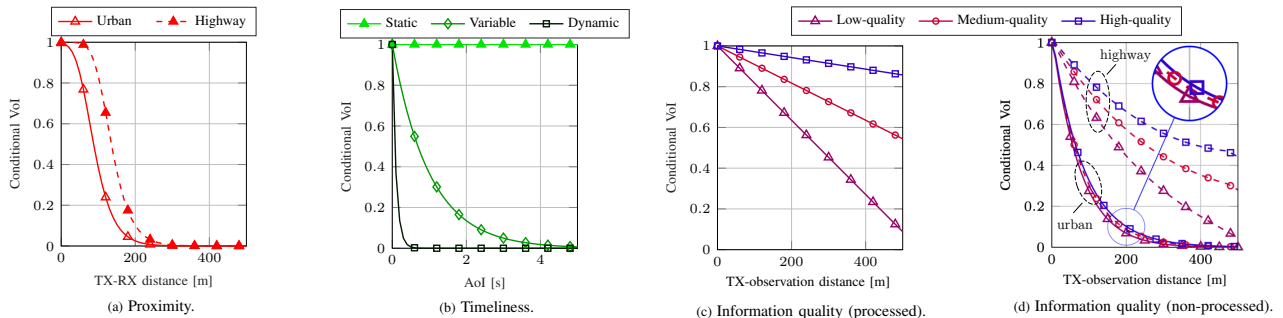
Fig. 2: Conditional VoI for space proximity, timeliness and information quality attributes. The plots show the impact of the TX-RX distance, the AoI, the TX-observation distance, the propagation scenario, the type of observation and the type of sensor.
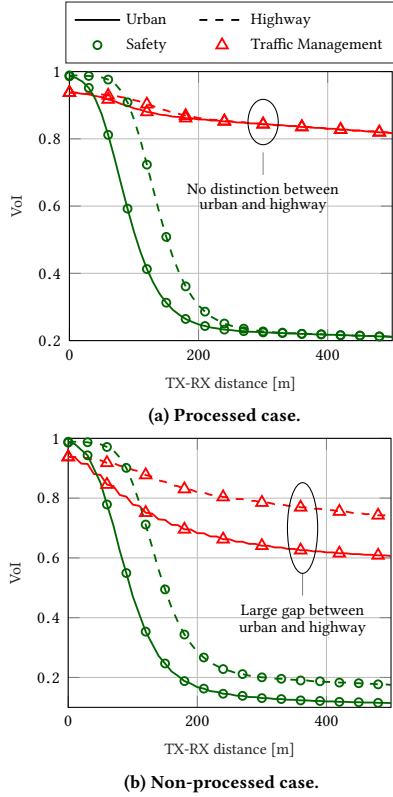
(a) Processed case.

(b) Non-processed case.

Fig. 3: VoI vs. TX-RX distance for urban and highway scenarios for processed and non-processed strategies. $P_{td} = 1$, $r_h = 1080$ px, AoI = 100 ms.

In Fig. 2c and Fig. 2d we plot the conditional VoI for the quality attribute, considering both processed and non-processed value assessment strategies, respectively. In the non-processed case the conditional VoI exhibits a significant difference between urban and highway scenarios. This gap is due to the higher probability that the line of sight is blocked in urban scenarios, in which case the image captured by the camera would be basically useless.

Phase 3 results – *overall VoI*. Our goal is to assign a value to different sources of information (in this work we consider camera observations) in such a way that the utility to potential receiver(s) is maximized. In Fig. 3 we evaluate the impact of the propagation scenario on VoI. First, we observe that, for safety applications, the value of data transmission at short distances is high in all considered conditions, reflecting the importance of maintaining fresh and updated information among close-by vehicles. Second, we see that, for traffic management services, VoI is almost independent of the TX/RX distance (proximity weight $w_2 = 0.0549 \ll 1$), demonstrating the importance of sharing LDM updates even at large distances. Third, we notice that, for safety services, VoI drops for values of d larger than 100 m, which is a rather safe inter-vehicle distance (in particular, in urban scenarios): transmitting data beyond this range would just increase the channel access contention without bringing much benefit in terms of safety. We can also observe that, in general, VoI for the considered information is higher in highway than in urban scenarios, because of the higher probability of LOS between object and sensor (camera). In general, the non-processed case (Fig. 3b), although guaranteeing real-time value determination,
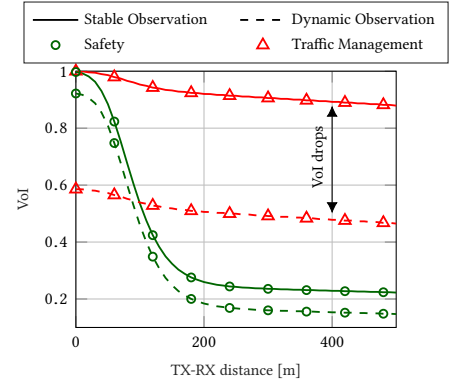

Fig. 4: VoI vs. TX-RX distance for different types of observations. Processed VoI operations, r_h =1080 px, AoI=100 ms, urban scenarios are considered.

(a) Static observations.
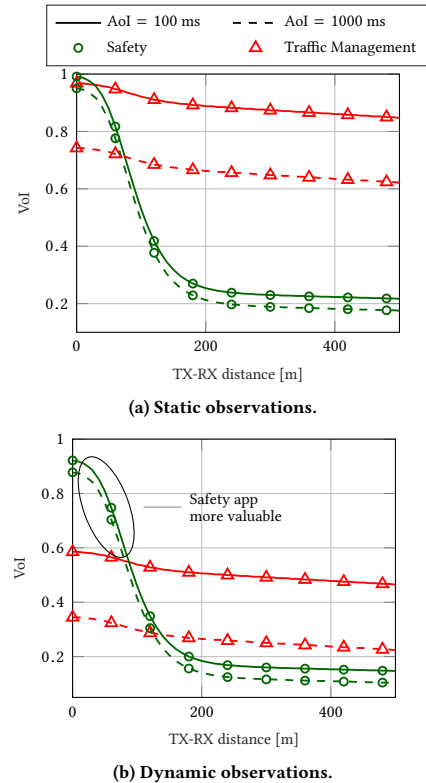

(b) Dynamic observations.

Fig. 5: VoI vs. TX-RX distance and AoI, for different types of observation. Processed VoI operations, r_h = 1080 px, urban scenarios are considered.

represents a lower bound for VoI in vehicular networks, as it provides a probabilistic, rather than deterministic, method to assess VoI. Moreover, for the non-processed case, different characterizations of the quality attribute in urban and highway scenarios (see Fig. 2d) result in different overall VoI: for traffic management applications, the gap is as large as 25% when $d > 200$ m, i.e., when the endpoints are in NLOS.

The following results are derived considering processed VoI assessment operations. In Fig. 4 we investigate how VoI evolves as a function of the type of observation. We observe that dynamic information is likely to have value for safety applications (although VoI eventually drops to zero at large distance): the gap between static and dynamic, i.e., short-lived, observations is less than 10% for
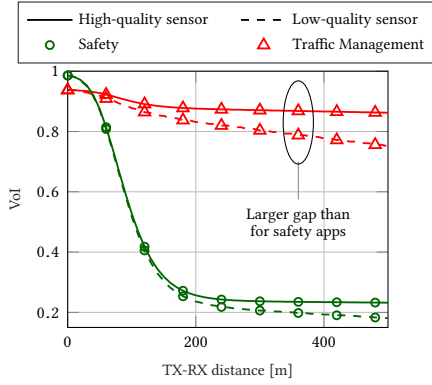
Fig. 6: VoI vs. TX-RX distance for different types of sensors. Processed VoI operations, $P_{td} = 1$, AoI = 100 ms, urban scenarios are considered.

$d < 100$ m. Conversely, the large impact of the timeliness attribute in traffic management operations (the weight is 0.6554) makes VoI decrease as much as 65% considering dynamic (as opposed to static) observations. This makes sense as time-varying perception records might become obsolete by the time they are actually transmitted.

In Fig. 5 we plot VoI as a function of the AoI and the sensor reading's temporal characteristics. Ideally, we would like information to be received as timely as possible, i.e., at the same instant it was generated by the source. However, real-world constraints, first and foremost the restricted network capacity, put a limit on the frequency at which status updates can be broadcast, thereby making the AoI larger than the inter-transmission time. For safety services, both "new" (i.e., AoI = 100 ms) and "old" (i.e., AoI = 1000 ms) information provide comparable value to the receiver(s), as long as short-range communications are considered. The reason is that even old perception records may still potentially increase the opportunity for vehicles to make object detections, a critical pre-requisite for safety-related operations. For traffic management services, instead, the impact of the AoI is very strong. "Old" information (i.e., AoI = 1000 ms) may, in fact, decrease VoI by more than 70% considering dynamic observations (Fig. 5b). To avoid the decay of information, such systems require very frequent updates to be disseminated through inter-vehicular communications, possibly causing, however, channel access problems. We notice that, for the dynamic case, VoI considering traffic management applications is below 0.6 even at short distances: at $d = 10$ m, VoI = 0.58 vs. VoI = 0.92 for safety applications, thereby validating the results in Fig. 4.

The patterns we observed in the previous plots can be recognized also in Fig. 6, which illustrates VoI evolution for different types of sensors. We see that VoI increases proportionally to the camera resolution, even though the effect of the sensor quality is not very significant: the gap between high- and low-quality sensor readings is below 15%. This is consistent with the outcomes of the AHP comparative evaluations, which assign very low priority weight to the quality attribute. In fact, although the network requires context information to be reliable, it still needs to prioritize timely dissemination to spatially close neighbors to prevent communication failures. Nevertheless, we observe that sensor quality degradation has a bigger impact on traffic management than on safety services (i.e., $w_3 = 0.2897$ vs. $w_3 = 0.1336$, respectively). Finally, Fig. 6 acknowledges the higher VoI for safety operations compared to traffic management at short distance.

5 CONCLUSIONS AND OPEN CHALLENGES

Despite the consensus about using VoI-aware solutions to reduce link overload, how to actually realize this is still a largely unexplored issue. In this paper we investigated for the first time the concept of VoI in vehicular networks and proposed a method that quantifies the expected VoI based on time, space and quality interdependencies. We evaluated the impact of the operating distance, the type of observation, the type of sensor, the propagation scenario and the age of information on the value assessment. Moreover, we numerically showed the rate at which VoI decreases considering obsolete, time-varying and inaccurate observations.

In this work we demonstrated the feasibility of considering VoI as a proxy for broadcasting decisions in vehicular networks. As part of our future research, we will validate our framework in dynamic scenarios and investigate the impact of other types of object features (e.g., the road structure) on the end-to-end network performance. Moreover, we will extend our implementation considering feedback messages from the receiver(s) and learning strategies.

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