Accuracy and Relevance: A Value of Information based Prioritisation of Perceived Objects for the ETSI Collective Perception Service

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***Abstract*—The Collective Perception Service (CPS) enables connected vehicles and infrastructure to share real-time sensor data to augment situational awareness, including the positions, speeds, and attributes of detected objects. While such updates provide valuable information, frequent and potentially redundant transmissions can result in saturation of the vehicular communication medium. To alleviate this, the European Telecommunications Standards Institute (ETSI) specifies a set of object inclusion rules governing Collective Perception Message (CPM) generation, which are largely based on dynamics or update frequency, as well as many additional update rate control (URC) measures that further suppress object reports. Due to the origins of these rules, largely based on cooperative awareness messages, this has resulted in a series of overly complex mitigation measures to limit the channel occupancy. As a result, there is a need to streamline CPM object inclusion rules into a singular Value of Information (VoI) based function that should, at the very least, expressly consider a) the perception accuracy of the information being shared and b) the importance of the data to the nearby Intelligent Transport System Stations (ITS-S'). It should rank and prioritise objects in a CPM in the presence of noisy sensor readings under diverse channel conditions. Based on discussions with the ETSI Collective Perception Service (TS 103 324) working group, this paper proposes the requirements and range for such a function and discusses the object states that would meet these requirements. It proposes and evaluates two possible VoI function implementations and shows that objects are more accurately ranked and prioritised than with current CPM rules. This informs more detailed VoI-based object inclusion function implementations in the future.**

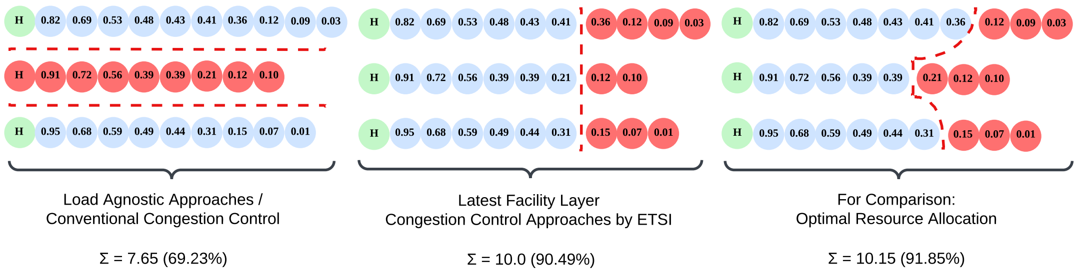
***Index Terms*—Collective Perception Service (CPS), V2X, Sensor Data Sharing, Value of Information (VoI).**

I. Introduction

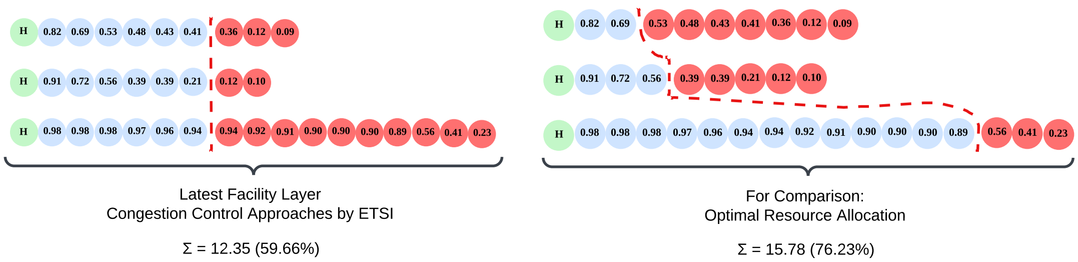
The ETSI Collective Perception Service [1] allows for real-time data sharing amongst ITS stations (ITS-S) that improves detection of hidden obstacles and non-connected road users, supports infrastructure-based observational operations through strategically placed sensors for critical driving scenarios, expands the available data pool by integrating inputs from multiple ITS-S' and ensures that real-time clearance information about drivable regions can be shared. It thus contributes to safer navigation, better traffic management, and more informed decision-making. Current Collective Perception Message object inclusion rules emerged as a variation of the dynamics-based rules originally devised for Cooperative Awareness Messages (CAMs) [2]. Subsequently, ETSI has proposed additional VoI-based URC mechanisms to 'patch' the frequency and redundancy challenges associated with the object inclusion rules. This has resulted in a complex plethora of possible ETSI URC filtering approaches [1] as well as methods to limit the frequent transmission of CPMs containing only a few objects [3], [4]. It has also been shown in the literature that approaches can contradict each other, necessitating even more complex functions to enable compatibility [5]. Furthermore, during the CPS assembly stage, if message size dictates fragmentation of the CPM, a utility function is necessary to further rank and prioritise objects, making the current ETSI CPM object inclusion process highly complex.

Separately, onboard object tracking sensors such as cameras, radar and LiDAR may produce noisy or inaccurate readings, especially under adverse environmental conditions or certain hardware limitations. As current ETSI object inclusion rules are mainly based on dynamics and age-based criteria with static thresholds, sensor noise may frequently trigger these conditions, resulting in frequent transmissions of data that is of little value to receivers. Reporting of noisy objects that do not contribute to enhanced perception negatively affects the overall channel load, an already documented challenge for collective perception [4], [6], [7], [8]. As current VoI-based URC methods act as an additional filtering mechanism after the object inclusion rules have decided, the candidate set of objects to possibly include, they prove ineffective.

This motivates the need for a single streamlined VoI-based object inclusion function that is capable of ranking and prioritising objects based on their a) perception accuracy and b) relevance to potential receivers. The contributions of this paper are (i) identification of the range and requirements that such a VoI-based function should fulfil, as well as the object states that meet these requirements, and (ii) specification and evaluation of two possible VoI-based function implementations. The proposed approach prioritises accuracy and relevance, particularly when channel access is restricted. It ranks objects



(a) Homogeneous Knowledge.



(b) Heterogeneous Knowledge.

Fig. 1: Resource Allocation Challenge with (a) Homogeneous and (b) Heterogeneous Knowledge. Smarter VoI-aware resource allocation mechanisms based on quality fairness are possible if VoI can be correctly ranked based on perceptual accuracy and relevance to potential receivers.

and selects only the most relevant ones for transmission based on the channel capacity. Performance is evaluated across a set of representative objects with diverse mobility and sensor noise characteristics. The performance of the proposed VoI function is evaluated against the current ETSI object inclusion rules and the *dynamics-based* update rate control mechanism.

II. Relevant Background

A. ETSI CPM Object Inclusion Rules

ETSI generation rules bound CPM transmission frequency within minimum and maximum thresholds. Within these intervals, CPMs are sent when object inclusion conditions are met, according to object type. For Type-A objects e.g. a single or group of vulnerable road users (VRUs), e-bikes etc, the main inclusion criterion is the detection frequency; for Type-B objects e.g. vehicles, motorcyclists etc, it is their dynamism. If a new **Type-A** object is detected or an existing Type-A object has not been included in a CPM for $\geq 500ms$, it is included. **Type-B** objects are also included if a new object is detected or if the last inclusion time $\geq 1000ms$. Otherwise, it is included if it fulfils one of the following criteria: position change $\geq 4m$, speed change $\geq 0.5m/s$ or heading change $\geq 4°$.

B. ETSI CPM Update Rate Control

ETSI's latest CPS specification also defines eight additional URC methods to derive VoI [1]. When many objects qualify for inclusion, an ITS-S can rank each object by its perceived "value" and prioritise accordingly if the channel is congested. In essence, objects with higher VoI scores i.e. those deemed most important, are sent first, while lower-ranked objects may be deferred or omitted if necessary to reduce the message size or frequency. This idea forms the basis for the latest ETSI Facilities layer congestion control approach [9] that sets a CPS quantity-based VoI threshold for object inclusion capacity (N) based on the CPM frequency and size, and limited by the $bits/s$ rate specified by the Bandwidth Management Entity (BME). It does not specify how the VoI should be calculated.

This can be seen in Fig. 1a, where each circle represents an object with a certain VoI value. Each row can represent either separate ITS-S' vying for the same communication medium in the same time interval or a single ITS-S with multiple objects to transmit over several timesteps. In Fig. 1a (middle), a VoI-based "quantity" filter represents the latest ETSI congestion control approach and is considered in CPS specifications. This prioritises the objects with the highest VoI for transmission and achieves higher collective VoI (10.0) than traditional load-based congestion control approaches (7.65) but for the same radio resource allocation. On the right of Fig. 1a, we can see the potential for specifying even better VoI-aware "quality" based filtering based on a VoI value threshold rather than a VoI quantity threshold. Importantly, while this offers only marginal benefit for homogenous knowledge, which assumes every ITS-S has a similar number of objects with similar VoI values, it can be utilised to more intelligently allocate resources if there are significantly more objects in terms of volume and diverse VoI value i.e. heterogenous knowledge, as shown in Fig. 1b. This can achieve much better utilisation of the channel to send more accurate, highly relevant objects (15.78) as well as quality fairness rather than quantity fairness. However for such intelligent VoI-based resource allocation mechanisms to be devised, there is a need for a VoI computation function based on relevance to the receiver and accurate ranking of sensed objects based on perceptual accuracy.

C. Literature Review

Some researchers have endeavoured to investigate VoI computation methods that explicitly consider the value of the data to be shared. The *value-anticipating* method introduced by Higuchi et al. [10] defers or drops object updates when the expected gain is low under congested network conditions so that higher-value data is prioritised. This is based on the Kullback-Leibler divergence but does not explicitly study the impact of inaccurate or noisy sensor measurements.

Assuming a suitable ranking of messages can be achieved at the originating station, Bansal et al. [11] proposed a weighted variant of the well-known LIMERIC congestion control algorithm [12] that allows each ITS-S to adapt its own β parameter in a distributed way based on the resources that it requires i.e. prioritising ITS-S with high VoI information. If considered with the approach proposed in this paper, this has the potential to deliver a smarter quality-based VoI filter, as shown in Fig. 1.

Few studies have addressed the impact that noisy measurements have on the invocation of the CPM object inclusion rules, thereby contributing to high network load and dissemination of imperfect sensing data. Li et al. [13] is the closest to what is proposed. The authors first filter noisy sensor measurements based on the covariance matrix trace, which is then compared against a static threshold that must be tuned based on the object's mobility. This will not account for diversity in moving objects, but the authors only consider a homogenous set of objects. The authors then attempt to further filter objects based on an entropy threshold using Kullback Leibler divergence, but they do not explicitly consider the appropriate ranking or prioritisation of diverse objects within a CPM. Wolff et al [14] empirically validate the impact of inaccurate sensor readings on ETSI inclusion rules which shows increased CPM size and tracking error.

III. Proposed Value of Information (VoI) based Object Inclusion Function

It is clearly beneficial to accurately rank objects based on a combination of sensing accuracy and relevance to others. Such a function would take the first steps to consolidate the existing object inclusion rules, URC mechanisms and utility function into a single effective process. Thus the challenge is to identify a means of deriving such a VoI function.

A. VoI Pipeline and Function Requirements

The pipeline for such a VoI function is shown in Fig. 2, containing two separate KF-based tracking processes, i.e. the Local Environment Model (LEM), and the V2X Exchanged Information (VEI) environment model. The VEI environment model represents the fusion of all received V2X and local knowledge exchanged over the network and should not be confused with the V2X measurement from surrounding ITS-S' or with the ITS-S global model that contains all of the knowledge, not just that transferred over the network.

In Fig. 2, the LEM continuously predicts and updates object states using measurements, whereas the VEI Environment Model independently tracks objects from received V2X messages that may or may not have been fused with LEM data from the previous timestep. Both models feed the KF output into the VoI function, which derives a value by meeting the requirements in Fig. 3 and comparing to one of the states shown in Fig. 4. Next, it assesses whether the object's VoI is within the CPS transmission rate threshold. If the LEM decides to transmit an object, the VEI KF performs an additional update step using the received LEM information.

We identify three core requirements to derive the VoI function representing the entropy between the LEM and VEI, including how their mutual agreement or disagreement should affect the VoI.

1) **The higher the LEM knowledge, the higher the VoI:** As the originating station's LEM state becomes more certain (i.e. lower covariance estimation uncertainty), the VoI should increase, indicating that the information is valuable to share with others.
2) **The higher the network knowledge (VEI), the lower the VoI:** As the VEI Environment model state becomes more certain, the VoI should decrease. This means that surrounding vehicles or infrastructure already have very reliable information about an object through their own sensors or from others, thus sending an update provides little new value and only contributes to channel load.
3) **The higher the disagreement between the LEM and VEI, the higher the VoI**: As the Euclidean distance increases between the LEM and VEI estimated state vectors for the same object, the VoI should increase but only to the extent that it truly provides new insight. A large LEM–VEI disagreement flags a potential inconsistency in perceptions, thus including such an object may be useful to resolve differences across vehicles' views.

The third requirement is optional because a VoI function may or may not explicitly account for disagreements in object state estimates by allocating it a higher VoI. Another way to express the VoI requirements is shown in Fig. 3. This defines the range of any candidate solution for the VoI function, with that range determined by the requirements. The equation components highlighted in red fulfil requirement 1 if the VoI is negatively correlated with the LEM covariance matrix. The equation components shown in green fulfil requirement 2 if the VoI is positively correlated with the VEI covariance matrix. Finally, the component highlighted in orange fulfils requirement 3 if the VoI is positively correlated with the mean difference between the LEM and VEI state estimates, whereas the component in blue does not as the VoI is uncorrelated.

It is useful to consider the possible relative states of the LEM and VEI environment models when evaluating what conditions a VoI function will be able to correctly rank and

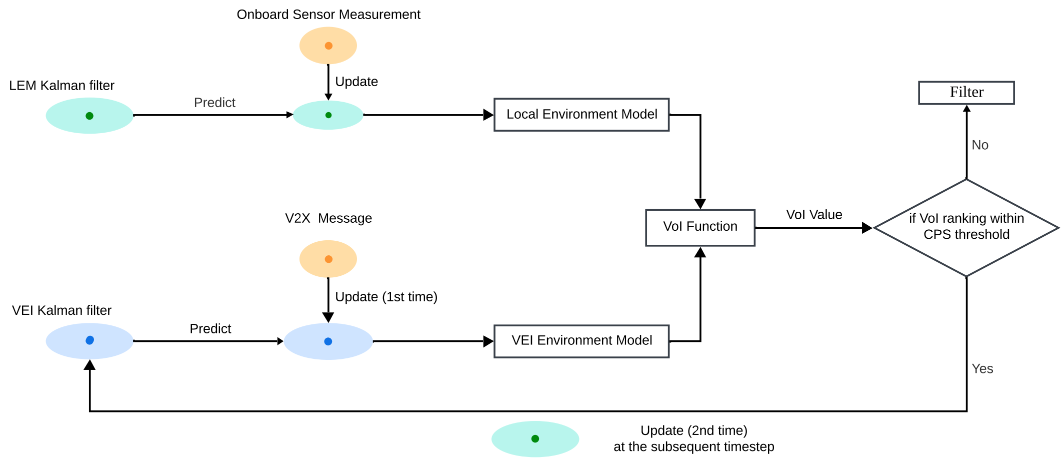
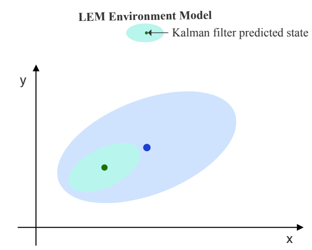


Fig. 2: Overview of the VoI-based Object Inclusion Pipeline.

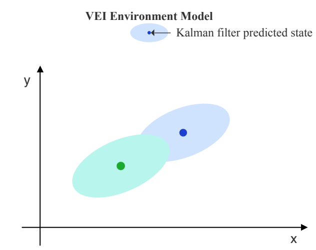
$$\text{def } VoI \,\Big|\, \left\{ \boxed{\frac{\partial \text{VoI}}{\partial|\Sigma_{LEM}|} < 0} \wedge \boxed{\frac{\partial \text{VoI}}{\partial|\Sigma_{VEI}|} > 0} \wedge \boxed{\frac{\partial \text{VoI}}{\partial|r_{LEM}-r_{VEI}|} > 0} \right\} \quad (1)$$

$$\text{def } VoI \,\Big|\, \left\{ \boxed{\frac{\partial \text{VoI}}{\partial|\Sigma_{LEM}|} < 0} \wedge \boxed{\frac{\partial \text{VoI}}{\partial|\Sigma_{VEI}|} > 0} \wedge \boxed{\frac{\partial \text{VoI}}{\partial|r_{LEM}-r_{VEI}|} = 0} \right\} \quad (2)$$

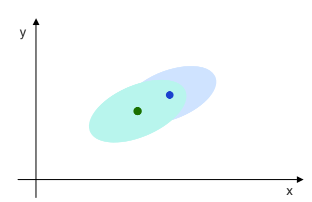
Fig. 3: Requirements of the VoI function that (a) consider both mean state deviation and covariance entropy (Eq. 1) or (b) isolates covariance entropy only (Eq. 2).



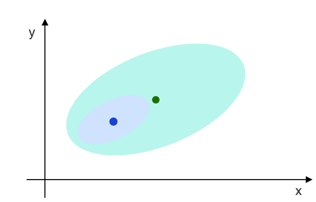
(a) **State A:** LEM's uncertainty is lower than V2X uncertainty.



(b) **State B:** LEM and V2X have similar uncertainty, but largely deviating predicted state positions.



(c) **State C:** LEM and V2X have similar uncertainty and similar predicted state positions.



(d) **State D:** LEM uncertainty is greater than V2X uncertainty.

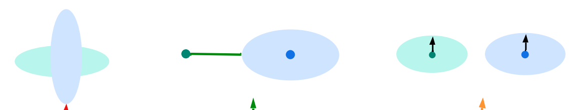
Fig. 4: Estimated object states from the perspective of the originating station's LEM vs the V2X estimated state.

prioritise. Fig. 4 illustrates the LEM and VEI perception states of four objects, labelled A-D, showing the Kalman filter (KF) ellipses for the state estimates and certainty. Based on the defined requirements, these states can be ordered by descending VoI priority, i.e. object states A-D are ranked with VoIs of 1^{st} to 4^{th} respectively. Specifically, in State A, the originating station's LEM uncertainty ellipse is much smaller than the VEI ellipse, indicating that the originating station has a very reliable object state estimate while others are relatively uncertain – thus the sensed object measurement may be of high value to potential receivers. This fulfils requirement 1 and yields the highest VoI. State D represents the converse; the LEM's uncertainty is greater than the VEI i.e. the VEI ellipse is smaller, meaning the collective perception of that object is already quite certain. This fulfils requirement 2 for a low VoI. In short, an object detected by the originating station with high certainty and low remote certainty (State A) is most likely to be transmitted, whereas an object known well to others, offering little new information (State D) is least likely. State B depicts a situation where the LEM and VEI uncertainties are similar, but their predicted state positions differ significantly. This disagreement or conflict could raise the VoI if the function accounts for it (requirement 3). State C shows the LEM and VEI with similar uncertainty and only a very small difference in their estimated state – essentially, the originating station and others agree on the object. In this scenario, the VoI is lower than State A and B, yet higher than State D.

B. Proposed Methods for the VoI based Object Inclusion Function

The requirements and operation of such a VoI-based function have been described. Next, two candidate solutions to satisfy the identified requirements in Equations 1 and 2 in Fig. 3 are detailed. The first option, *Kullback Leibler Divergence (KLD)*, considers both uncertainty reduction and state discrepancy between the originating station's local estimate and the VEI estimated state i.e. requirements 1-3 inclusive. The second approach, *Expected Covariance Divergence (ECD)*, focuses exclusively on uncertainty differences i.e. requirements 1 and 2 only. We observe in subsequent sections that KLD does not meet requirement 3 under certain conditions.

1) Option 1: Kullback–Leibler Divergence (KLD): The KL divergence [15] provides a measure of how a Gaussian proba-



$$KLD = \frac{1}{2}\left[\boxed{tr(\Sigma_{LEM}^{-1}\Sigma_{VEI})} + \boxed{\left((r_{VEI} - r_{LEM})^T \Sigma_{VEI}^{-1} (r_{VEI} - r_{LEM})\right)} - K + \boxed{\log\left(\frac{det(\Sigma_{VEI})}{det(\Sigma_{LEM})}\right)}\right] \quad (3)$$

Fig. 5: KLD for VoI derivation. The formula components represent the ellipse shape/stretch in red (covariance matrices trace), mean state difference in green (squared Mahalanobis distance), and ellipse' areas in orange (determinant).

bility model differs from another. As shown in in Equation 3 in Fig. 5, the KL expression is comprised of three parts. Two of these capture the change in uncertainty (covariance) between the VEI model and the LEM model. This is the product of the traces of the covariance matrices (red in Fig. 5) that indicate the ellipse shape, and the log-determinant ratio term (shown in orange). These two terms primarily govern requirements 1 and 2: if the LEM's covariance Σ_{LEM} is smaller (more precise) than Σ_{VEI}, the log-determinant ratio is positive and the trace term remains moderate – the result is a higher VoI, fulfilling the 1st requirement. Conversely, if Σ_{VEI} is smaller (the VEI information is more precise), the log-determinant term becomes negative and the trace term grows larger, together reducing the VoI and fulfilling the 2nd requirement. The 3rd component in Fig. 5 is the squared Mahalanobis-distance (green), which is the distance in standard deviations between the mean of the LEM state estimate and the mean of the VEI distribution. It measures how far apart the two state estimates are in terms of the uncertainty of the VEI model. Because it accounts for the shape and size of the uncertainty ellipsoid (scaling the distance by the standard deviation of the VEI covariance), it is preferable to a simple Euclidean distance as it allows for direct comparison/ranking between different types of objects that exhibit different dynamics and levels of sensor noise. In principle, a larger Mahalanobis distance indicates a large discrepancy between the LEM and VEI state estimates that could raise VoI, thereby addressing the 3rd requirement. However, this term does not always perfectly reflect the Euclidean disagreement as shown in Fig. 6. If the VEI uncertainty is very large in a certain direction, a large Euclidean gap in that direction might only yield a small Mahalanobis distance, which could lower the VoI. Thus, while the KLD VoI function inherently includes a mean-disagreement component, it may or may not strongly increase VoI depending on the VEI covariance geometry.

2) Option 2: Expected Covariance Divergence (ECD): We distinguish between KLD, which includes both mean and covariance differences between distributions, and ECD, which isolates the entropy between the LEM vs VEI object certainty. The second candidate VoI function only seeks to meet the first 2 requirements identified in Section III-A. Thus, it focuses exclusively on the uncertainty ellipsoid comparison and does not consider the difference in state estimates, i.e. it removes the Mahalanobis-distance term (shown in green in Fig. 5).

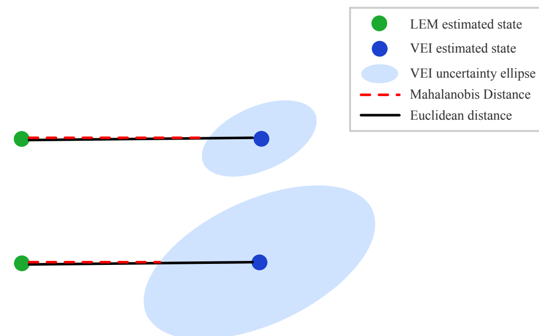


Fig. 6: Impact of the shape and size of the uncertainty ellipsoid on the Mahalanobis distance for the same Euclidean distance. This can impact the derivation of the VoI value.

The trade-off is that it guarantees responsiveness to sensor confidence levels, i.e. States A and D, avoiding potential inconsistencies from the Mahalanobis distance calculation, illustrated in Fig. 6. The results of both options are normalised as per Equation 4, resulting in a VoI ranging from 0 to 1. The closer the value is to 1, the more beneficial it is to surrounding ITS-S', and the closer it is to the state described in Fig. 4a.

$$VoI = \frac{KLD}{1 + KLD} \in [0, 1). \quad (4)$$

An operational application of both KLD and ECD is demonstrated in [14], where their effects on tracking performance and channel load are empirically evaluated.

IV. Simulation Environment

A traffic scenario with six objects is simulated to represent three distinct road user types: moving cars, pedestrians, and parked cars. Key parameters are summarised in Table I. Moving cars follow predefined trajectories with speeds ranging from 0 up to approximately 90 km/h. Pedestrians can move up to 1.5 m/s in a random walk pattern while the parked cars remain stationary at fixed locations. The process noise magnitude in the motion model varies by object type: moving cars use a factor of 1, pedestrians 0.1, and parked cars 0.01. It is important to note that the volume of objects is not of great importance for this study. Rather, object pairs have been chosen based on their characteristics i.e. a diverse and typical set of objects with differing dynamics and exhibiting low and high sensor perception accuracy. Thus, this covers the identified States (A-D) and should be applicable to real-world conditions. The characteristics of these objects are shown in Table II.

Object sensor measurements are generated at 10 Hz, reflective of typical real-world sampling rates. All measurements are modelled by adding Gaussian errors on the ground truth state vector (x, y, v_x, v_y) of the object. Within each object category, one object has low LEM sensor noise and high V2X sensor noise, while the other object has the opposite configuration. In other words, for each pair of objects (cars, pedestrians, parked cars), one object simulates accurate local perception

TABLE I: Simulation Parameters.

Parameter	Moving Car 1	Pedestrian 1	Parked Car 1	Moving Car 2	Pedestrian 2	Parked Car 2
Speed range	90 km/h	1.5 m/s	-	90 km/h	1.5 m/s	-
Low Sensor Noise:	$(x,\, y,\, v_x,\, v_y) = (1.0,\, 0.7,\, 0.2,\, 0.3)$					
High Sensor Noise:	$(x,\, y,\, v_x,\, v_y) = (5.0,\, 6.0,\, 2.0,\, 2.4)$					
Process noise factor	1	0.1	0.01	1	0.1	0.01
Trajectory	Predef. Path (Straight+arc)	Random walk	Stationary	Predef. Path (Straight+arc)	Random walk	Stationary
Simulation duration	180 s					
Measurement frequency	10 Hz (sensor measurement rate)					

TABLE II: Object Characteristics.

Object	Type	Sensor Accuracy	Description
Object 1	Fast vehicle (1)	High LEM Precision Low V2X Precision	Detected with high precision (low sensor noise) by ego-sensors but poorly reported by V2X network (high sensor noise).
Object 2	Pedestrian (1)	High LEM Precision Low V2X Precision	
Object 3	Parked vehicle (1)	High LEM Precision Low V2X Precision	
Object 4	Fast vehicle (2)	Low LEM Precision High V2X Precision	Detected with low precision (high sensor noise) by ego-sensors but precisely reported by V2X network (low sensor noise).
Object 5	Pedestrian (2)	Low LEM Precision High V2X Precision	
Object 6	Parked vehicle (2)	Low LEM Precision High V2X Precision	

with noisy V2X data, and the other object simulates noisy local perception with accurate V2X data. This setup is designed to test whether the candidate Voi functions respond appropriately to different perception conditions by giving higher importance to data that complements poor local data and lower importance when local sensing is already reliable.

Three scenarios with different channel conditions are evaluated: Idle, Moderate, and Saturated. To simulate [9] that proposes a VoI-based quantity filter, a threshold N is set. In the *Idle* scenario, it is considered that the communication channel has full capacity to transmit CPMs containing all objects ($N = 6$). The *Moderate* channel scenario has up to 66% capacity i.e. up to four objects per CPM ($N = 4$) and the *Saturated* scenario only has 33% capacity i.e. only two objects can be transmitted ($N = 2$).

V. Evaluation

For the objects shown in Table II, it is clear that transmission priority decreases with increasing object number. Fast-moving vehicles need frequent updates for safety. Pedestrians are unpredictable, so they need higher inclusion rates. Parked cars are stationary and require fewer updates. Across all object categories, objects with high measurement accuracy that are of interest to other ITS-S' should be ranked with higher VoI. Thus any proposed VoI function should prioritise object inclusion based on this order, especially if filtering is required in the case of channel congestion. In this section, we evaluate the performance of the ETSI object inclusion rules, the ETSI dynamics-based URC method and our proposed VoI-based function using the *KLD* and *ECD* implementations, under varying sensor accuracy and channel conditions to investigate if objects can be sorted in a meaningful way. The *dynamics-based* method calculates the absolute Euclidean distance between the local sensor measurements and V2X sensor measurements for the same object and gives objects with larger differences in distance a higher ranking.

A. Analysis of ETSI Object Inclusion Rules

As described in Section II-A, Type A objects e.g. pedestrians, are reported based on frequency alone whereas Type B objects e.g. vehicles and motorbikes, are reported based on both dynamics and frequency. Thus, irrespective of inaccurate sensor measurements, it can be observed from Figure 7 that pedestrians 1 and 2 are included in CPMs with the same rate. Current rules also do not take into account the state of the channel when choosing to include an object in a CPM. This can be observed across Figures 7 - 9 inclusive, as the object inclusion rates do not change irrespective of channel state. Importantly, current rules do not rank objects by importance/priority. This can also be observed when noisy Type B objects are repeatedly broadcast even when the information adds little new value. Specifically, it can be observed that moving car 2 is included in CPM updates with 68.7% more frequency than moving car 1 due to inaccurate sensor measurements. More consequential is the frequent reporting of parked cars, irrespective of whether they incur low or high sensor noise, which illustrates how the current criteria can propagate redundant information. This is due to the frequent triggering of the heading 4° change threshold that causes the parked cars to be included in almost every update. Fig. 10 illustrates differential heading errors versus object speed under varying sensor velocity noise levels as well as the ETSI CPM 4° heading threshold. At low speeds, heading errors sharply increase due to velocity sensor noise dominating the heading estimation. Consequently, even minor sensor noise triggers this threshold at speeds below 3.56m/s, and this triggering speed

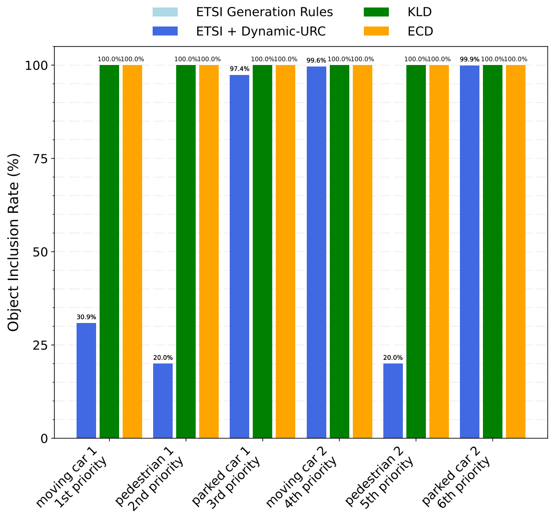


Fig. 7: *Ideal Channel State:* Number of times each object is included in a CPM as a function of different inclusion rules.

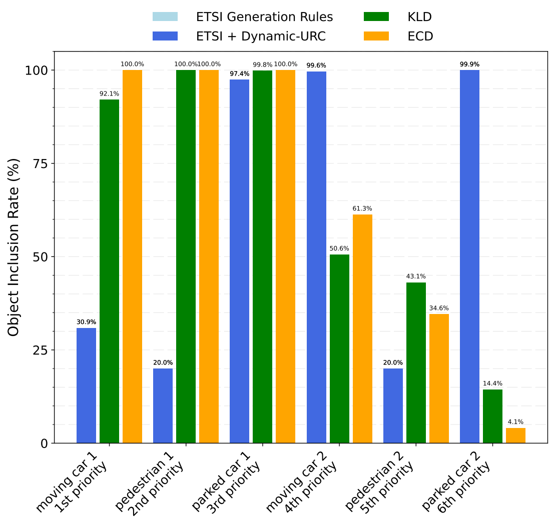


Fig. 8: *Moderate Channel State:* Number of times each object is included in a CPM as a function of different inclusion rules.

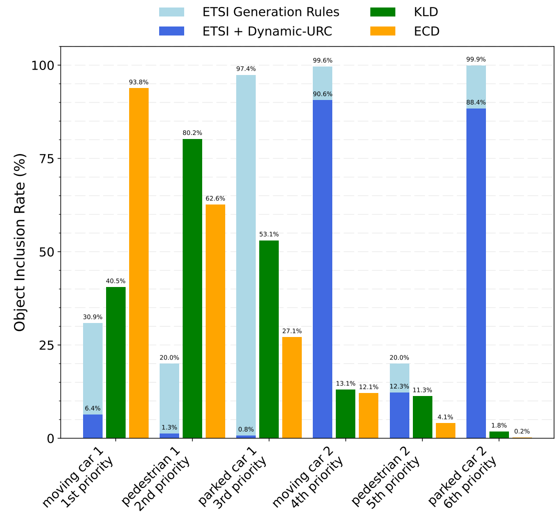


Fig. 9: *Saturated Channel State:* Number of times each object is included in a CPM as a function of different inclusion rules.

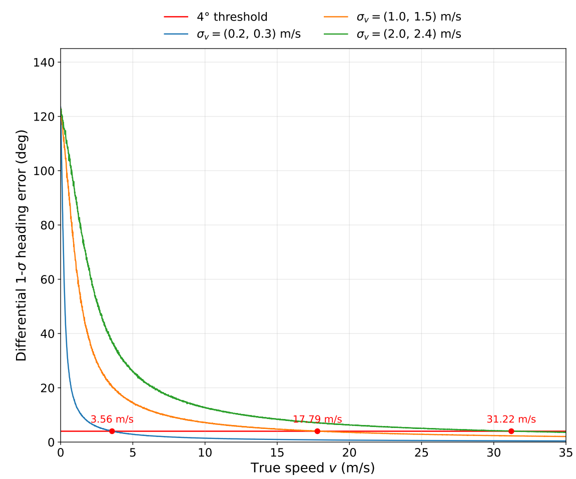


Fig. 10: Relationship between velocity and differential 1σ heading error for three sensor velocity noise levels.

significantly increases as sensor noise rises. In summary, if the object speed is low the ETSI heading rule is most likely to be triggered, and thus this is more susceptible to noise.

B. Analysis of ETSI Dynamics-Based Update Rate Control

The additional dynamics-based URC mechanism offers little improvement over the object inclusion rules. In the simulations, it was observed that the number of objects included in each CPM under ETSI object inclusion rules has a mean of 3.71. Thus, under a CPS quantity-based threshold (moving average) based on frequency and size, for an *idle* channel with 100% capacity ($N = 6$ for 6 objects) and *moderate* conditions with 67% capacity ($N = 4$), the number of objects already remain within the allowable channel capacity. Thus, the dynamics-based URC has no impact as there is no need to filter any objects. Under *saturated* channel load with only 33% capacity ($N = 2$), the URC still performs poorly. This is because it ranks objects by the Euclidean distance between the LEM and V2X sensor readings. Objects with large measurement discrepancies, typically caused by sensor reading inaccuracies, remain highly ranked. Consequently, when only two objects can be included, the algorithm often retains noisy, low-value objects and filters out more useful ones, as shown in Fig. 9.

C. Analysis of Proposed VoI-Based Object Inclusion Function

The proposed VoI-based inclusion rules adapt the VoI based on the perception accuracy and the value of each object. Under *idle* channel conditions, both *KLD* and *ECD* include all objects in the CPMs with high frequency, as shown in Fig. 7. Since the channel can accommodate the reporting of up to six objects, such frequent updating is acceptable – it maximises overall awareness for nearby ITS stations, even if some updates are based on noisy data. ETSI is separately investigating a pre-filter mechanism to remove noisy/inaccurate sensor measurements that cannot be well associated with an object track.

In the *moderate* and *saturated* scenarios, the VoI approaches behave as intended by curtailing unnecessary updates. Fig. 8 and Fig. 9 show that objects with high LEM noise (parked car 2 and other noisy objects) see far fewer inclusions under both KL variants. Importantly, the algorithms automatically prioritise the most relevant information: only the highest-VoI objects (typically those that are less predictable or whose states are not already reliably known by others) continue to be frequently sent. Lower-VoI objects, such as parked car 2, are largely filtered out when the channel is limited. Since other ITS-S' already had a reliable estimate of this stationary object and the local sensor's data is uncertain, the VoI is low. This demonstrates how the VoI-based function prioritises high-value updates. Both KLD and ECD outperform the ETSI object inclusion rules and the dynamics-based URC, delivering more efficient channel use in every tested scenario.

An interesting observation can be made when directly comparing the performance of *KLD* with *ECD*. In Fig. 8 and Fig. 9, *KLD* under-reported moving car 1, one of the highest priority objects. The reason for this is attributable to the squared Mahalanobis distance component of the KL formula that does not always grow when the Euclidean distance between the LEM and VEI estimated states increases as shown in Fig. 6 and explained in Section III-B1. This can occasionally reduce the calculated object VoI, causing several moving car 1 updates to be filtered under more congested channel conditions. However, the *ECD* approach does not consider the difference between the LEM and VEI state estimates, thus attributing higher VoI and including the object more frequently in CPM updates. Aside from this edge case, both VoI-based methods aligned the object update frequency with its actual information value.

VI. Conclusions & Future Work

This paper investigated the shortcomings of ETSI CPM object inclusion rules and URC mechanisms in prioritising transmission of high-value objects and proposed a VoI-based function to correctly rank and prioritise objects based on their perception accuracy and importance to receivers under different channel conditions. As expected, the legacy ETSI rules sort the objects imperfectly, ignoring their priorities/relevance. The ETSI dynamics-based URC mechanism performs even worse, especially under high channel loads. *ECD* and *KLD* result in better channel usage, with *ECD* performing marginally better than *KLD*. Both correctly rank objects while accounting for the knowledge of surrounding ITS-S' under restricted channel conditions, which would allow for smarter VoI-aware resource allocation mechanisms in the future.

Future work should thoroughly investigate the performance of these functions in real-world conditions. Specifically, the impact of false tracking associations and track management. Inaccurate sensor measurements can lead to false object track associations which can make the KF less reliable i.e. incorrectly decreasing the uncertainty ellipsoid which may result in unexpected VoI rankings. Furthermore, if a new object is sensed by coming into range or returning from an occlusion, the large uncertainty ellipse associated with a new KF track may lead to a lower VoI ranking. It remains to be investigated whether this should be the case or if newly sensed objects should be automatically included as is currently the case in ETSI rules. Future work may also consider the number of independent sources and the Automotive Safety Integrity Levels (ASIL)/Safety Integrity Level (SIL) levels of the information on the VoI ranking.

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