A Spatial Model for Using the Age of Information in Cooperative Driving Applications

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ABSTRACT

The age of information (AoI) has been proposed as a metric for evaluating freshness of information; recently also within the context of intelligent transportation systems (ITS). The most frequently used definition of age of information (AoI), however, does only account for the generation time of the data but not for application-specific aspects. In intelligent transportation systems (ITS), for example, the distance of vehicles is not considered and nodes farther away may experience an increased age of information (AoI) due to effects of the wireless communication channel. We propose a new way of interpreting the age of information (AoI) in such a context, also considering the location of the transmitting vehicle as a metric of importance to the information. In particular, we introduce a weighting coefficient used in combination with the peak age of information (PAoI) metric to describe the age of information (AoI) requirement, emphasizing on packets from more important neighbors. As an example, we characterize such importance using the orientation and the distance of the involved vehicles. We use the derived model to focus on timely updates of relevant vehicles for meeting a given age of information (AoI) requirement, which can save resources on the wireless channel while keeping the age of information (AoI) minimal.

CCS CONCEPTS

• **Networks** → *Application layer protocols*; **Network performance modeling**; *Network simulations.*

KEYWORDS

Age of information, vehicular networking, cooperative driving, intelligent transportation systems, spatial model

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1 INTRODUCTION

Intelligent transportation systems (ITS) are becoming more feasible, and we see first deployments. Vehicles can now do real-time monitoring of the surrounding environment to detect objects such as other vehicles or pedestrians. Furthermore, vehicle-to-everything (V2X) communication technologies such as IEEE 802.11p, which is often referred to as distributed short-range communication (DSRC), and celluar V2X (C-V2X) allow exchanging of information with other vehicles or roadside infrastructure. This enables cooperative driving applications such as, among others, Intersection Collision Avoidance (ICA), cooperative perception, media sharing, or platooning, which bring a whole set of new features and services to today's driving [6].

For such applications to work correctly, fresh information from and about surrounding vehicles is required (i.e., up-to-date). Due to the inherent mobility of ITS, such information may become outdated or even incorrect and eventually no longer relevant to an application because of position changes. To ensure up-to-date information, update messages (*beacons*) are typically sent at regular intervals. An example is the transmission of cooperative awareness messages (CAMs) [7], which are foreseen both in the IEEE 802.11p-based ETSI ITS-G5 standard as well as in C-V2X.

In order to quantify and to characterize the freshness of such information, a metric complementing raw delay, loss, and throughput measures would be helpful. Recently, the concept of the age of information (AoI) has been explored [11, 24] for this. The AoI evaluates the freshness of information and balances the trade-off between the timely information update and communication resources. Thus, the AoI directly addresses the freshness of received packets, which in turn accounts for the process of emission and delays introduced in the communication chain, all-together [24]. Inherently, this distinguishes AoI metrics from conventional delay metrics [13] allowing to optimize the network freshness as the best balance between throughput and delay. In this context, often the peak age of information (PAoI) is used as a measure to indicate worst case situations.

In early work on AoI in the vehicular context, the average AoI and the PAoI are used to find the best strategy for the emission rate of beacon packets [10]. However, this approach does not focus on the message content [23]; not all packets necessarily carry the same information's importance, thereby not introducing the same level of freshness for the status update. Let us use the intersection depicted in Figure 1 as an example. The status updates of the vehicles in front of vehicle 1 (i.e., vehicles 2 and 3) are clearly more important to avoid potential collisions than those from the other vehicles (i.e., vehicles 4, 5, and 6). Thus, for vehicle 1 to avoid collisions at this intersection, it is preferable to collect updated information about

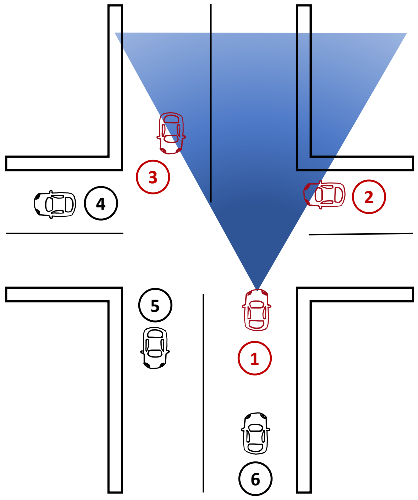

Figure 1: Example scenario: Vehicles in the direction of movement of vehicle 1 (vehicles 2 and 3) are more relevant than others (vehicles 4, 5, and 6) when considering a safety application such as Intersection Collision Avoidance (ICA).

vehicles 2 and 3. Correspondingly, an AoI-based metric should also consider this application-dependent context. Some reported studies address the information's content when measuring the AoI. Examples include techniques to best predict *Markovian* sources in [9], to better synchronize cache content with the remote source [25], to account for only new arrived information [13, 15], and to use information-theoretic approaches for reduced uncertainty about the source [24].

In a different approach, we propose a new way of interpreting the AoI for arrived packets, which is directly applicable in the context of ITS. In this formulation, we consider the transmitting vehicle's location as a metric to quantify importance of the information. We emphasize such importance in the form of weighting coefficients that are used on the average PAoI metric as well as on the general AoI requirement. These coefficients provide some level of selectivity for the received packets, which allows for treating vehicles' information more selectively. Thus, using our model allows focusing on timely updates of relevant vehicles for meeting a given AoI requirement instead.

Our contributions to this work can be summarized as follows:

- We propose a spatial model for interpreting the AoI of received packets based on the spatial location of the transmitting vehicle, making AoI context specific.
- We evaluate the AoI and the impact of our model on individual communication links.
- We show that using our model helps controlling the beacon rate necessary for achieving a given AoI requirement.

2 AGE OF INFORMATION IN ITS

Following the standard IEEE 802.11p, we already see a number of studies that address the use of AoI metrics for time-critical applications in vehicular networks [1–3, 10, 12, 14]. The AoI metric is reported to update the network freshness for the exchange of vehicles' speeds and positions. Some of these works provide closed-form expressions for the AoI metric [1–3, 14], while other works estimate the average AoI metric numerically [10, 12].

Using analytic methods, the resulting average AoI metric is formulated mainly in two different approaches. On one hand, Lyamin et al. [14] straightly formulate the average AoI as the average of the time duration between two consecutive received packets. They assume that the time duration distributes according to the joint event where two transmissions do not collide in the channel. The channel collision probability is evaluated according to the formulation provided by Vinel et al. [22].

On the other hand, the average AoI is evaluated using the formula for the remaining service time in a queue [1, 2] and considering the hidden [1, 2] and non-hidden node problem scenario [3]. In the hidden node scenario, the time duration of message transmissions is expanded, assuming that hidden nodes transmit independently with a random phase between 0 and the transmission duration parameter. In the non-hidden scenario, Andrea et al. [3] also derive a formula for node and network levels. The node-level accounts for the average AoI at any arbitrary node, assuming they only transmit the most recent packet. The network level evaluates the case where nodes do not transmit new packets till the current one is sent. In this case the network is modeled according to a Markov chain model, the transition probabilities can be derived as described in [22].

In a different direction, based on simulation results, the existence of a unique beacon period minimizing the average AoI is illustrated for a certain number of vehicles, and contention window (CW) sizes [10]. Following these results, a rate control algorithm is derived from adapting the broadcast period based on local measurements of the average AoI. The vehicle reduces or increases the beacon period by comparing it to the estimated average AoI metric looking for the maximum network freshness.

All the above studies conduct simulations based on the IEEE 802.11p standard for single-hop [1, 1, 2, 10, 14] and multi-hop [1, 10, 12, 12] networks. Besides, a variety of scenarios for the traffic of vehicles have been studied. Examples include four lane roads [10], platooning [12, 14], the more artificially Manhattan Grid [1, 2], the TapasCologne scenario [1, 2], and open environments [3].

However, these reported solutions are only addressing protocol parameters (e.g., beacon rate, CW size) and the channel impact like collisions and noise to formulate the average AoI metric. Minor focus is formulated in terms of the contextual meaning of information [16]. In this direction, Michalopoulou et al. [16] seek to minimize the information aging in the spatial dimension when evaluating the product of the speed of the vehicle and the time duration between received packets. The information age is reduced by stating the optimization problem in the spatial domain to minimize the predicted-location error.

In a different approach, we introduce a degree of importance in the AoI metrics concerning the intended direction of the vehicle and its surrounding. In the form of weighting coefficients as formulated by Sorkhoh et al. [20], we incorporate into the average PAoI metric the vehicular context (direction, surrounding), looking for some meaning of received beacon packets [11]. In doing so, we study the PAoI metric weighting as more critical for those vehicles in the direction of movement (cf. Figure 1) and with less importance

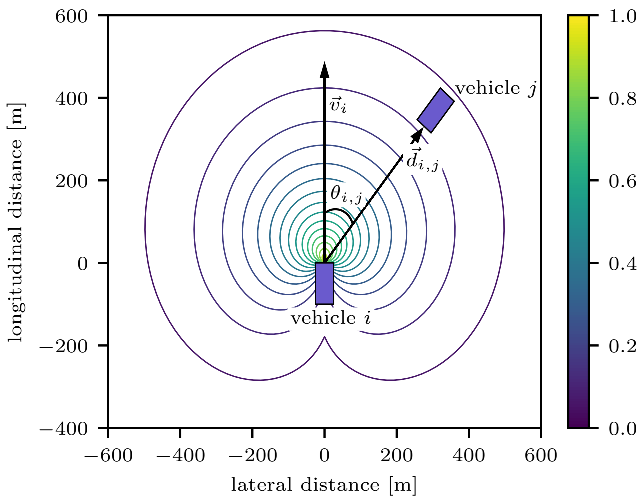

Figure 2: Visual representation of our spatial model for calculating the weighting coefficient used for the AoI interpretation with an example configuration of $\alpha = 0.75$, $\beta = 0.005$.

otherwise, when considering a safety application such as ICA [5] as an example use case. We use this modified PAoI metric and compare it to a similarly modified AoI requirement of 100 ms, which is often used in literature as desired update interval [8, 17]. We thus identify how many vehicles have fresh information, similar to using the original AoI definition.

3 A SPATIAL MODEL FOR THE AOI

Typically, the AoI metrics are measured per user irrespective of their location. All the packets received from surrounding vehicles are treated with equal importance. However, the level of importance is application dependent: E.g., while in platooning only the members of the platoon itself are relevant, it is the surrounding vehicles within the direction of movement that are important for safety-related applications such as ICA. As one example use case, Figure 1 thus shows such an intersection scenario. Here, the most valuable information for vehicle 1 will be located in the direction of its movement (shadowed area). Thus, vehicles within this area (i.e., vehicles 2 and 3) should be assigned a higher level of importance than other vehicles in the surrounding. Beacon packets coming from vehicles in the rear of the intended direction will not be that informative about the traffic in the intended direction of vehicle 1. Therefore, vehicles in front will be more demanded to reduce the corresponding AoI metrics than the vehicles in the rear. Since all vehicles are equal in the standard AoI, frequent beacon transmissions from the less important vehicles can lead to unnecessary channel load in this case. If the communication protocol was aware of this application-specific level of importance, it could update the periodicity of the beacons in accordance and eventually reduce the load on the wireless channel.

3.1 Weighted Peak AoI

To consider the location of the transmitting vehicle as a metric of importance to the information, we propose a new way of interpreting the AoI. To that end, we introduce a weighting coefficient that is applied to the PAoI metric as well as to an AoI requirement, emphasizing on packets from important vehicles. Thereby, we introduce some level of selectivity for the received packets which allows to treat vehicles' information differently according to the importance to the application. Our model can be easily adjusted to the requirement of a specific application through parameters and does not modify the underlying AoI metric itself.

We choose the weighting coefficient as a raised-cosine function with a decay factor as

$$\omega_{i,j} = \frac{1}{2}\left(1 + \cos(\alpha\theta_{i,j})\right) e^{-\beta\|\vec{d}_{i,j}\|} \tag{1}$$

where $\theta_{i,j}$ is the angle between the transmitting vehicle j and the direction of movement of vehicle i and $\| \vec{d}_{i,j} \|$ is the distance between both vehicles, while α and β are two coefficients to select the degree of selectivity in the spatial domain. The coefficient α provides selectivity in the radial direction, while β in the azimuth direction. The larger the value of α or β is, the narrower is the beam of vehicle i. Figure 2 shows a visual representation of our weighting coefficient with an example configuration of $\alpha = 0.75$, $\beta = 0.005$.

To derive the angle and the distance between vehicles, we assume that vehicles are equipped with global positioning system (GPS) receivers, and that this information is exchanged between vehicles in periodic beaconing messages. Using the configuration in Figure 2, $\omega_{i,j}$ is close to 1 whenever vehicle j is in the direction of movement of vehicle i. Otherwise, it is close to 0 whenever vehicle j is away, being 0 when vehicle j is located at the rear of vehicle i.

With this coefficient, we measure the importance of the introduced age per received packet using the average PAoI metric as

$$\Delta_{i,j}^{(\omega)} = \omega_{i,j}\Delta_{i,j}^{(p)}, \tag{2}$$

where $\Delta_{i,j}^{(p)}$ denotes the average PAoI metric for a link between vehicles i and j. Correspondingly, the combined PAoI per vehicle i will be calculated after averaging the perceived $\Delta_{i,j}^{(p)}$ as

$$\Delta_{i}^{(\omega)} = \frac{1}{N-1}\sum_{j=1}^{N-1} \omega_{i,j}\Delta_{i,j}^{(p)}. \tag{3}$$

Finally, we account for the network operation after averaging for the total of nodes as

$$\Delta^{(\omega)} = \frac{1}{N(N-1)}\sum_{i=1}^{N}\sum_{j=1}^{N-1} \omega_{i,j}\Delta_{i,j}^{(p)}. \tag{4}$$

The average PAoI ($\Delta_{i,j}^{(p)}$) can be derived by analytical or numerical means through simulators. Analytically, it can be obtained after calculating the expected average of the inter-arrival (Y_n) and system time (T_n) as $\Delta_{i,j}^{(p)} = \mathbb{E}\{Y\} + \mathbb{E}\{T\}$ when all packets emitted are received [23]. However, some packets will not be successfully received due to the system and channel conditions (e.g., collisions, replacement of the old beacon frames, low reliability during their reception, etc.) [22]. Taking into account the impact of the system and channel effects in the packet reception process, as given by the successful probability P_{sd}, the average PAoI can be calculated as

$$\Delta_{i,j}^{(p)} = \frac{1}{P_{sd}}\mathbb{E}\{Y\} + \mathbb{E}\{T\}, \tag{5}$$

where the value for P_{sd} in Equation (5) can be directly computed considering the impact of noise and collisions using the closed-form expressions in [22, Eq. (7)], or through simulations.

The Equation (5) can be directly computed by recalling the use of the negative binomial distribution as described in [21]. However, it can be intuitively derived based on the meaning of the related variables in Equation (5). P_{sd} can be interpreted as the ratio of successfully transmitted packets; thus, its inverse will provide the total of attempts to have a successful transmission. Therefore, the first term in Equation (5) will provide the waiting period before a packet is successfully transmitted. Adding the average time spent on the system ($\mathbb{E}\{T\}$) will thus provide the average PAoI.

3.2 Remarks

The introduced coefficients in Equation (3) provide a mean to "filter" packets according to their relevance. For instance, in the intersection scenario depicted in Figure 1, the average PAoI of packets from the vehicles 4, 5, and 6 will be lowered as less relevant, thus emphasizing those packets from vehicles at the front side of vehicle 1 (vehicles 2 and 3). In this way, the resulting average PAoI will be characterized the most by those links of interest according to the application context.

Equation (3) is also useful in different ITS scenarios, and, also with a different dependency for the coefficients other than Equation (1). Overall, the Equation (3) comprises a mean to emphasize some communication links in contrast to others. Once the links of interest are determined, they will shape the resulting average PAoI whenever their corresponding coefficients are close to 1. In contrast, those links whose coefficients are close to 0 will not contribute to the age of information metric.

Besides, we selected the dependency of the coefficients with the spatial coordinates in Equation (1) as a two-dimensional function in two separable terms. One dimension for the azimuth direction defines the raised-cosine function [4], which conveniently allows multiplying by 0 to those packets coming from the rear side of vehicle i. The second dimension is in the radial direction and defines a decay factor, which decrements as long as the distance increases. Overall, both terms let to a function that is also all-orders differentiable, which accounts for its mathematical tractability.

3.3 Weighted Target AoI

The derived weighted PAoI metric can be used to fairly evaluate the freshness of the status updates with a given target, i.e., when the age of received packets is less than a given threshold. This approach is particularly relevant when we want to save resources looking at the PAoI metric just performing below a given threshold $T_{i,j}$ (target). In this way, we avoid the network to operate on the minimum average where demanding resources are higher. We compare the derived average PAoI with a given threshold, after applying the same weighting coefficients (cf. Equation (1)) as well, yielding

$$\Delta_i^{(\omega)} \leq \frac{1}{N-1} \sum_{j=1}^{N-1} \omega_{i,j} T_{i,j}. \tag{6}$$

Correspondingly, we account for the network operation after averaging for the total of nodes as

$$\Delta^{(\omega)} \leq \frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{j=1}^{N-1} \omega_{i,j} T_{i,j}. \tag{7}$$

Further discussions on the utility of these expressions and their interpretation are given within Section 4.

4 EVALUATION

In this section, we evaluate the PAoI as well as the impact of the weighting coefficient from our spatial model in simulative experiments using the Veins simulator [19]. First, we provide an initial analytical assessment of our model. After that, we consider simulative results and discuss the impact of the link distance on the standard PAoI. We continue selecting two specific link distances (i.e., a short and a long one) and analyze the combined PAoI without and with our spatial model. Next, we show the impact of our spatial model on the network PAoI. Finally, we analyze the impact of the model parameters on the network PAoI.

4.1 Initial Analytical Assessment

Providing further intuition on the impact of the coefficient $\omega_{i,j}$, we now perform an initial analytical assessment of the perceived average PAoI given by Equation (3). We compute it for a given link between 200 vehicles that are all moving randomly in a free-space grid. The corresponding communication parameters are listed in Table 1. To compute $\Delta_{i,j}^{(p)}$, we use Equation (5) where the probability of successful beacon reception P_{sd} is obtained from simulation (cf. Sections 4.2 and 4.3). We consider a contention-based communication system according to IEEE 802.11p, where vehicles broadcast beacon messages following a collision avoidance mechanism without retransmissions. Frames are emitted after verifying free channel access during the arbitration inter-frame space (AIFS) and CW time windows. We assume that only the most updated message is queued at the emitter side waiting for a free slot to be transmitted [1].

Figures 3 and 4 plot analytical results for the impact of the model parameters α and β, which define the degree of selectivity for computing the PAoI metric. The case $\alpha = 0$, $\beta = 0$ results in $\omega_{i,j} = 1$, i.e., no spacial selectivity at all, which corresponds to highest PAoI metric (standard definition from Equation (5)). However, as α and β increase, the perceived PAoI metrics are reduced due to the reduced importance of those vehicles not in the direction of movement and not that close to the moving vehicle (cf. link 1-5 in Figure 1). In this

Table 1: Parameters used for analytical evaluation

Parameter	Value
Scenario Size	550 m × 550 m
Simultaneous Vehicles N	200
Beacon Size L	512 Byte
Bitrate R	6 Mbit/sec
CW size W	4–8
Preamble duration T_{P}	32 µ sec
PLCP duration T_{PLCP}	8 µ sec
Propagation delay δ	1 µ sec
AIFS	58 µ sec

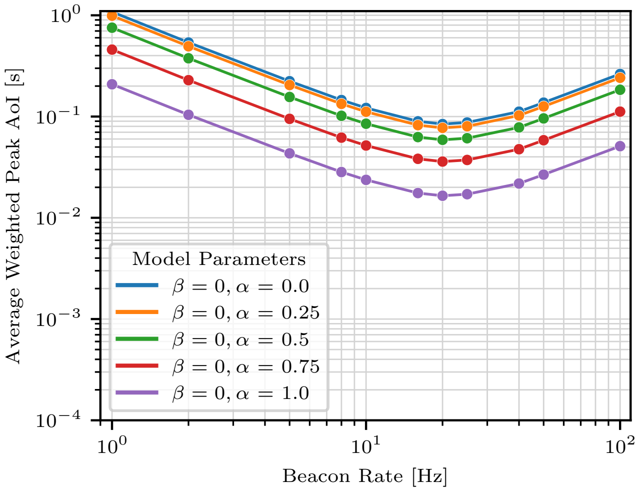

Figure 3: Average PAoI for different angle coefficients when $\beta = 0$. The spatial model only focuses on the angle.

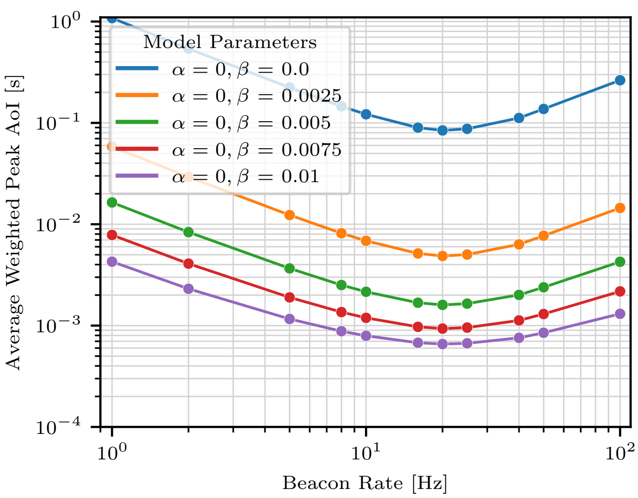

Figure 4: Average PAoI for different distance coefficients when $\alpha = 0$. The spatial model only focuses on the distance.

case, the contribution of the given link to the total PAoI in Equation (3) will become less, thus less critical. Comparing both figures indicates that the distance has a higher impact on the calculation of the weighting coefficient than the angle.

4.2 Simulation Setup

After the initial analytical assessment of our model, we now move on and consider simulative results. For our simulation, we use the well-known vehicular network simulation framework Veins [19] to enable a realistic evaluation. In particular, we use OMNeT++ 5.6.2, SUMO 1.6, and Veins 5.1. Tables 1 and 2 together summarize the most important parameters used in our simulations.

We focus on an urban simulation environment and, for simplicity, chose a 550 m × 550 m Manhattan grid scenario (see Figure 5). The scenario contains 200 vehicles that depart at random positions

Table 2: Additional parameters used for simulations

Parameter	Value
Scenario Type	Manhattan Grid
Beacon Rates	1, 2, 5, 8, 10, 16, 20, 25, 40, 50, 100 Hz
Carrier Frequency	5.89 GHz
Access Category	AC_VO
EDCA Queue Size	1
TX Power	20 mW
Attenuation Model	Free-space only ($\alpha = 2$)

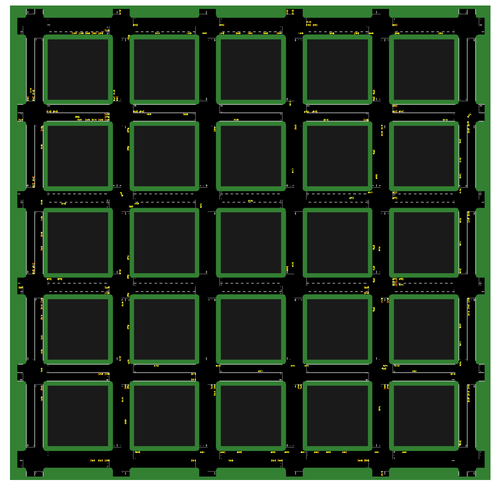

Figure 5: Manhattan grid with randomly distributed vehicles

and follow random trips. Vehicles are transmitting beacons such as CAMs via IEEE 802.11p at a static beacon rate. Within our simulation, we are able to switch off the attenuation effect of buildings by disabling the *obstacle shadowing* [18]. Furthermore, we modified the medium access control (MAC)-layer queue to replace the most recent packet if the maximum queue size is reached and a new beacon was generated from the application layer. Together with a queue size of 1, this results in always transmitting the most recent data in the beacon [1].

The data from the received packets including its generation and reception times is stored in a simple 1-hop neighbor table on every vehicle. We are thus able to calculate the standard AoI for a given link by using this time stamp of the last successfully received update. Whenever a new beacon from vehicle j is received by vehicle i, the data as well as the time stamp is updated and we record the PAoI as the current AoI value of this link at i. Similarly, we calculate the weighting coefficient according to Equation (1) for a particular link upon successful packet reception by using the sender's position from within the packet. From our simulation, we obtain, on average, a total of 1500 samples for PAoI and corresponding target AoI per vehicle and simulated beacon rate, which we are going to use for the following results.

4.3 Impact of Link Distance on Standard AoI

In order to underline the issues with the standard AoI, we first have a look at the impact of the link distance on the AoI. The PAoI, as defined in Equation (5), is influenced by the beacon rate (cf.

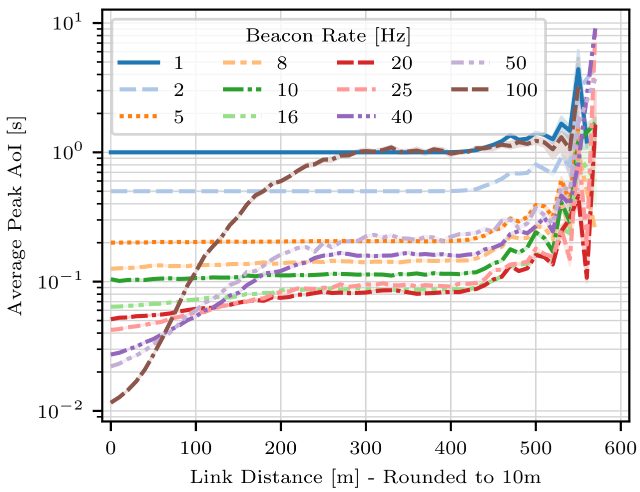

Figure 6: Average PAoI based on the link distance (rounded to 10 m) with different beacon rates

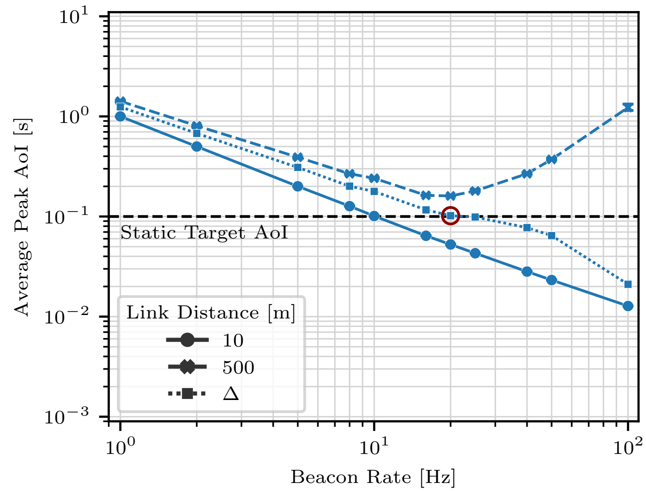

Figure 7: Average PAoI plotted for all as well as separated for two specific node distances (i.e., short and long). The red circle indicates the intersection of the average PAoI with the (static) target AoI of 100 ms.

$\mathbb{E}\{Y\}$), system delay (cf. $\mathbb{E}\{T\}$), and probability of successful packet reception (cf. $\frac{1}{P_{sd}}$). Thus, even if multiple vehicles use the same beacon rate for beacon transmission, the observed PAoI metrics can be very different due to the effects of the wireless communication channel, especially over large distances. Since the longest possible distance between two vehicles in our scenario is only about 780 m, we can neglect the system delay as an influencing factor.

The probability for successful reception of a packet, however, has to be considered. It depends on the signal-to-noise-and-interference-ratio (SNIR), which is, among others, influenced by scenario-related effects such as attenuation of the signal as well as interference from other vehicles. In our scenario, the signal is attenuated by free-space path loss, which weakens its strength proportional to the link distance. Also, at large distances, hidden nodes can introduce additional interference and collisions, which further degrades the SNIR. At some point, a packet cannot be received successfully anymore and the AoI of the corresponding link increases further until the next successful reception. Therefore, the link distance can have a huge impact on the PAoI, especially for far away vehicles.

Figure 6 shows the average PAoI per link distance (rounded to 10 m) with different beacon rates that we obtained from the simulation. Indeed, we see that the link distance has an impact on the PAoI according to our hypothesis described previously.

For small link distances (less than 50 m) and low beacon rates (e.g., 1 Hz), the observed PAoI closely follows the beacon interval (i.e., the multiplicative inverse of the beacon rate) as the signal distortion due to the impact of the wireless communication channel is minimal. However, at higher beacon rates (e.g., 16 Hz), the effect is increased and becomes visible more clearly. Latest at roughly 400 m, we start to see a massive increase in PAoI, which is way above the beacon interval. Here, the probability for a successful reception of a packet is so low that many updates are lost and the PAoI increases a lot. For very high rates (e.g., 40 Hz and above), the PAoI already steeply rises at even low distances of below 100 m. As a result, we see that, even when using the same beacon rate, two links can have a very different PAoI because of different node distances. Hence, the freshness of the information from close vehicles is typically much better than from those far away, as expected.

4.4 Combined Standard AoI

Consider an arbitrary cooperative driving application that requires regular updates from surrounding vehicles (e.g., ICA, cf. Section 3). This application will likely define a target AoI (i.e., maximum allowed AoI) that is required by the application to work successfully and reliably. In order to determine whether certain information is fresh enough, the average PAoI can be evaluated against this requirement. A typical update interval requirement that is often found in literature is 100 ms [8, 17]. Following the observation from the previous section, far away vehicles will always suffer from a weakened SNIR and thus have a higher PAoI compared to vehicles that are close. Thus, when combining the PAoI values from all surrounding vehicles using Equation (3), the far away vehicles will increase the average and thus distort the view on the overall information freshness.

Figure 7 shows the average standard PAoI of short (i.e., 10 m) and long (i.e., 500 m) distant links for several beacon rates. It also shows a static target AoI of 100 ms as well as the average of the PAoI values from the two links (cf. Equation (3)). As expected, the average PAoI of the short link distance (i.e., 10 m) continuously decreases proportional to the increasing beacon rate. Here, the minimum value, which indicates the best information freshness, is reached at the highest simulated beacon rate (i.e., 100 Hz. At this distance, the static target AoI of 100 ms is already reached at a beacon rate close to 10 Hz. This is expected, since 10 Hz is the multiplicative inverse of the target AoI and the PAoI is not distorted at these short distances (cf. Section 4.3).

When looking at the long link distance (i.e., 500 m), the situation is different: First, the average PAoI is decreasing similarly to the short link distance, following the increase of the beacon rate. But it never reaches the target AoI of 100 ms. Instead, after reaching its minimum at 20 Hz, the average PAoI increases when beacons are transmitted at higher rates. That is due to effects of the wireless communication channel described in Section 4.3.

When looking at the combination (i.e., average) of the two link distances, we can observe some interesting effects as well. First, the average PAoI value decreases as expected, but when increasing the beacon rate further, also its value decreases further, thus reaching the static target AoI of 100 ms at roughly 20 Hz (red circle). The continuous decrease even at higher beacon rates (i.e., above 20 Hz) is due to less received packets for the long distant link. Thus, the combined PAoI contains a lot more low values which have been observed from the short link distance.

When we now compare the beacon rates at which the static target AoI of 100 ms is met, we see that twice the beacon rate of the short distant links is required when combining the PAoI metrics from both distances. Hence, in order to keep the combined freshness of the information from all surrounding vehicles below the given AoI requirement, beacons need to be transmitted at a higher rate than required for close vehicles only. If vehicles now have different levels of relevance to the application, e.g., close vehicles are more important than far ones (cf. Section 3), the non-relevant vehicles (i.e., the far ones) will weaken the perceived combined information freshness. In order to meet the AoI requirement, all vehicles need to transmit their beacons at a higher rate, which leads to unnecessary transmissions and channel load.

4.5 Combined Weighted AoI

In order to cope with the issues of the standard AoI (i.e., effects of the wireless communication channel and equal importance of all nodes), we now apply the proposed spatial model from Section 3 to the AoI. Using Equation (1), we calculate the weighting coefficient ω for every PAoI value that is observed for an arbitrary link between two vehicles i, j, producing a *weighted PAoI*. Additionally, we also apply the weighting coefficients to the static target AoI of 100 ms on a per link bases, producing a *weighted target AoI*. Within this section, we use one exemplary parameterization (i.e., $\alpha = 0, \beta = 0.01$) of our spatial model that uses only the distance between vehicles for calculating the weighting coefficient. This focusses on the issue described in Section 4.3.

Figure 8 shows the average weighted PAoI of short (i.e., 10 m) and long (i.e., 500 m) distant links over several beacon rates. It also shows an average weighted target AoI as well as the average PAoI values from the two links, which can be used by application as a view on the overall information freshness. Since we selected fixed distances, the calculated weighting coefficient will be the same for all links of the same distance. The resulting average weighted PAoI is just a multiplication of the average standard PAoI from Figure 7 with a constant factor and thus follows a similar trend.

Due to the selected parameterization of our spatial model, a high (i.e., close to 1) and a low (i.e., close to 0) weighting coefficient is calculated for values of the short and long distant links, respectively. As a result, the average PAoI for the short distant links is very close to the one of the standard AoI from Figure 7, whereas it is reduced a lot for the long distant links. Therefore, and due to less observations

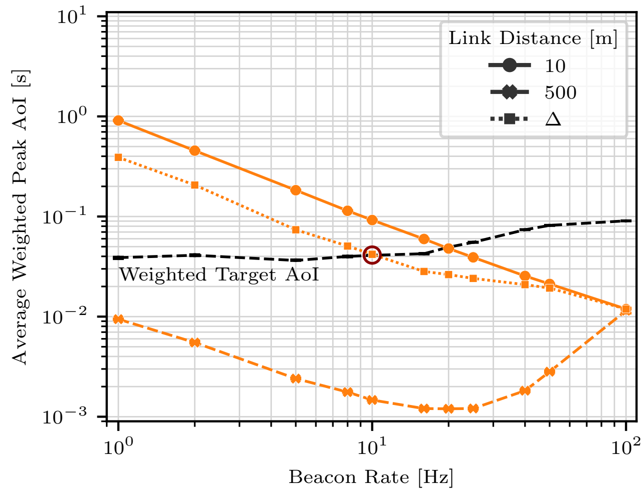

Figure 8: Average weighted PAoI for two specific link distances (i.e., short and long) and their combination (i.e., average). The red circle indicates the intersection of the combined PAoI with the weighted target AoI.

for the long distant links in general, the combination (i.e., average) of all PAoI values from both distances is, in comparison to Figure 7, much closer to the average PAoI of the short distant links. Thus, the overall view on the information freshness is not distorted much by the long distant and (in our parameterization) less relevant links.

The average weighted target AoI is constructed by combining all weighted target AoI values from the two link distances, similarly to the average weighted PAoI. Since the same weighting coefficients are applied to the PAoI and the target AoI, the target faces similar effects: For the short distance, the target is close to the static target AoI of 100 ms, whereas for the long distance, it is close to 0 due to the weighting coefficient being close to 0. The average weighted target AoI thus is close to the static target AoI of 100 ms as it is mostly influenced by short distant links. Note that the individual weighted target AoI for both distances is constant for all beacon rates as the link distance does not change and the beacon rate is not considered when calculating the weighting coefficient. The average weighted target AoI, in contrast, is not constant due to the increasing number of lost packets and thus less values for the long link distance with high beacon rates. The average therefore tends towards the value of the short link distance, when using a beacon rate ≥ 20 Hz.

When comparing the average PAoI with the target AoI, we see that now both link distances as well as their combination intersect with the target AoI at some point. The short distant links meet the target at a beacon rate close to 20 Hz. The average PAoI of the long distant links is below the weighted target AoI even for all beacon rates. This is due to the average weighted target AoI mainly begin influenced by the short distant links, thus, tending towards the static target AoI of 100 ms. Additionally, the weighting coefficient for the long distant links are close to 0. The combined weighted PAoI reaches the weighted target AoI at a beacon rate close to 10 Hz, as indicated by the red circle. This is a smaller beacon rate than required for only the short distant links due to the impact of the

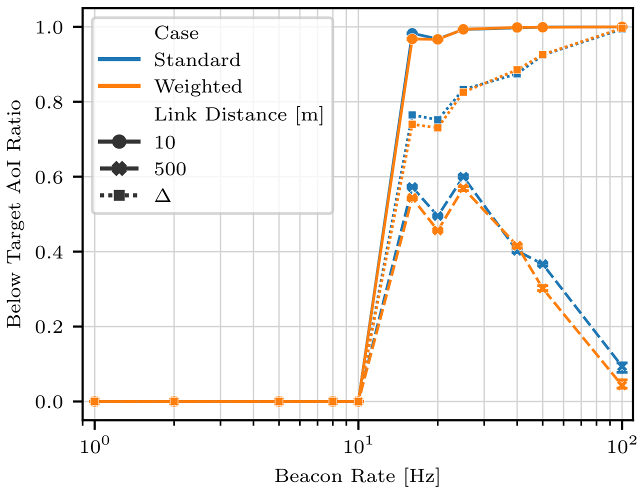

Figure 9: Ratio of vehicle updates that are below the target AoI for the standard case (blue) and when applying our spatial model (orange) – two specific link distances (i.e., short and long) and their combination (i.e., average).

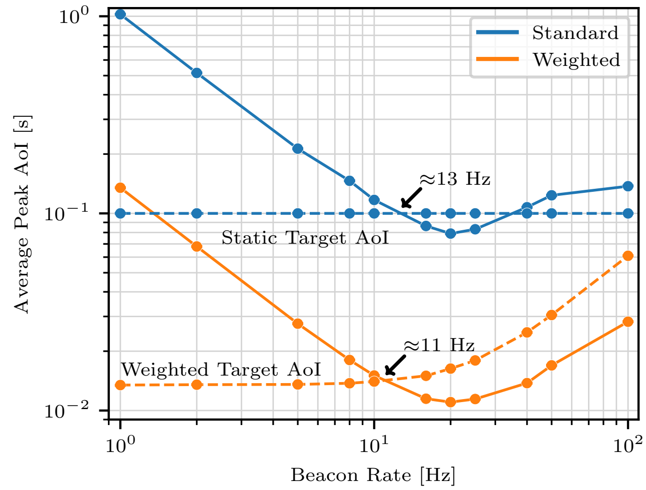

Figure 10: Average PAoI (solid) and corresponding target AoI (dashed) of the entire network for the standard case (blue) and when applying our spatial model (orange). The arrows indicate the intersection with the corresponding target AoI.

long distant links on the average. However, we actually need to compare this situation with the values from using the standard PAoI and the static target AoI in Section 4.3: With the spatial model, we only need half of the previous beacon rate to reach the target AoI when combining all link distances. Using our model allows to focus on timely updates of relevant vehicles for meeting a given AoI requirement instead, which saves channel resources.

4.6 Ratio of Links Reaching the Target AoI

The weighted coefficient which we introduced in Equation (6) allows interpreting the weighted PAoI in the way we interpret the standard one. To illustrate the validity of our approach, Figure 9 comparatively depicts the ratio of PAoI values fulfilling the condition in Equation (6) and the case using the standard approach, i.e., $\Delta_{i,j} \leq T_{i,j}$ without using the weighting coefficient. Without the spatial model, the target AoI is static at 100 ms, whereas when applying the spatial model, it is calculated by using the weighting coefficient (cf. Equation (6)).

The ratio for both cases is at 0 for all beacon rates $\leq$ 10 Hz. This is expected since the target AoI of 100 ms cannot be reached when the inter-arrival time of the beacons is larger than this value. When increasing the beacon rate further (above 10 Hz), all ratios are increasing as well. The ratios for the short link distance almost immediate reach 1 and stay there since these links have a very good SNIR and thus almost all transmitted beacons are received successfully, leading to a small PAoI. For the long link distance, the ratio grows as well but not as strongly as for the close links. Again, this is due to the weighted PAoI being impacted by the large distance of the link (cf. Figure 6), thus leading to many PAoI values being above the target AoI. Beyond 25 Hz beacon rate, the ratio for the long link distance decreases again due to a high PAoI (cf. Figure 8).

As expected, the combination of both link distances lies in between the short and the long distant links. After reaching roughly 0.75 at 16 Hz, its value increases until it reaches almost 1 at 100 Hz. This is due to the high number of lost packets for the long distant links, which leads to a value similar to the value of the short link distance.

It is visible that the ratio is very similar for both cases (i.e., standard and weighted). This reflects that the perceived status update on the network is the same irrespective of the weighting coefficients. Thus, using the formulation in Equation (7) will not introduce any artifact on the perceived network status; instead, it will just emphasize the relevant links.

4.7 Weighted Network AoI

So far, in order to show how our spatial model can influence the perceived average PAoI when combining different links, we have been looking at two specific link distances only. Now, we combine all available links from within the simulation scenario to analyze the average PAoI of the entire network. Again, we are evaluating the freshness of the information by comparing the average PAoI against the AoI requirement. This time, however, the goal is to determine the overall information quality of the entire network.

Figure 10 shows the average network PAoI (solid, cf. Equation (4)) as well as the corresponding network target AoI (dashed) for the standard case (blue) and when applying our spatial model (orange). We use the same parameterization of the spatial model as we did already in Section 4.5 (i.e., $\alpha = 0, \beta = 0.01$). The standard PAoI (blue) behaves as expected. It follows the beacon rate inversely proportional as the interval between beacons decreases with higher beacon rates. It intersects with the static target AoI of 100 ms at approximately 13 Hz (not simulated) and reaches its minimum value at 20 Hz. Since the average PAoI here contains the values from all available link distances (i.e., 0–600 m), there is indeed a minimum, which we can not observe in Figure 7. This is due enough successfully received packets with high PAoI values (mostly from long distant links) such that they can weaken the perceived average PAoI.

When looking at the weighted case (orange), the situation is similar but the absolute values of the average PAoI and target AoI are smaller due to the applied weighting coefficient. Note, that the minimum PAoI value is achieved at the same beacon rate in both cases, which underlines the applicability of our model without distorting the standard interpretation of the AoI. Similar to Figure 8, the target is calculated by combining all available individual target AoI values using the average function (see Equation (7)). It is almost constant and lower in comparison to the static target AoI at beacon rates ≤ 10 Hz due to many medium and long distant links that have a small weighting coefficient. At these low beacon rates, the packets from large distances can still be received successfully. When increasing the beacon rate beyond 10 Hz, analog to the average PAoI, the number of lost packets for medium and long distant links increases and the average weighted target AoI therefore tends towards the value of the short link distances. In the weighted case, the intersection of the average PAoI with the target happens already at approximately 11 Hz (not simulated), which indicates that this beacon rate is high enough to achieve the required AoI of the entire network on average. This approximated beacon rate is roughly 2 Hz lower compared to the standard case. Using our model thus allows to save channel resources by focusing on timely updates of relevant vehicles for meeting a given AoI requirement.

4.8 Impact of Model Parameters

In our simulative results, so far we have only looked at one exemplary parameterization (i.e., $\alpha = 0, \beta = 0.01$) of our spatial model that uses only the distance between vehicles for calculating the weighting coefficient. In fact, we used a very strict value for the distance parameter β, which was favouring very short link distances. In general, more relaxed configurations will lead to a higher weighting coefficient, thus, producing higher PAoI (cf. Section 4.1), especially for vehicles far away from the front of the receiver (i.e., in distance and orientation). Thus, we now compare the resulting average PAoI as well as the target AoI for different parameterizations of our spatial model.

Figure 11 shows the average PAoI (solid) and corresponding target AoI (dashed) of the entire network for different configurations of our spatial model (different colors). Here, we focus only on 4 different configurations:

(1) $\alpha = 0, \beta = 0$, which reflects the standard case by always using a weighting coefficient of 1 (blue),
(2) $\alpha = 0, \beta = 0.01$, which only focusses on the distance between vehicles for determining their relevance (orange, see previous sections),
(3) $\alpha = 1, \beta = 0$, which only focusses on the orientation (angle) between vehicles for determining their relevance (green),
(4) $\alpha = 1, \beta = 0.01$, which uses orientation (angle) and distance between vehicles for determining their relevance (red).

As expected, all configurations that apply our spatial model (i.e., 2–4) result in a decrease of the average PAoI and target AoI by filtering less relevant vehicles. We can observe, however, that using only the angle (2) results in a situation that is close to using the standard PAoI and the static target AoI (1). In contrast, using only

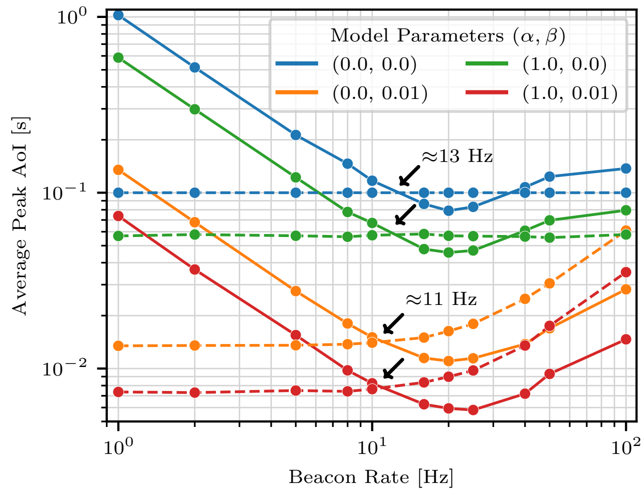

Figure 11: Average PAoI (solid) and corresponding target AoI (dashed) of the entire network for different configurations of our spatial model (different colors).

the distance (3) results in a situation that is close to using angle and distance together (4). Configuration which behave similarly also have a similar beacon rate at which the average PAoI is intersecting with the target AoI, i.e., approximately 13 Hz vs. 11 Hz (not simulated). This shows that the distance has more impact than the angle when calculating the weighting coefficient, which is in line with the theoretical results from Section 4.1. This is due to the effects of the wireless communication channel (cf. Section 4.3), which impact the PAoI quite heavily. Also, vehicles within the scenario are distributed in space rather than in the close surroundings of single vehicles.

4.9 Discussion

Within this work, we used a static target AoI of 100 ms, since this value is often used in literature as a desired update interval of data used by cooperative driving applications. This value, however, is arbitrary and can freely be configured dependent on the specific needs of the application. Our proposed spatial model is independent of the actual value for this target AoI, since the same weighting coefficient is applied to both, the observed PAoI values as well as the static target AoI. When modifying the value of the target AoI, the intersection point with the average PAoI will be shifted along the x-axes, leading to a different beacon rate that is sufficient for meeting the target. When the target value is increased, this beacon rate decreases and vice versa. In case both, a small target AoI and a low beacon rate, is desired, it can be beneficial, to use a stricter configuration of our spatial model (i.e., lager values for α and β). This will impose a greater selectivity in the importance of vehicles and cope with effects of the wireless communication channel as described in Section 4.3.

5 CONCLUSION

We explored the use of the age of information (AoI) in the context of intelligent transportation systems (ITS). First approaches of using the AoI in ITS focused on the original definition only, i.e., to measure the PAoIs for every received message and then to interpret the resulting values as they are. We, however, observed that this is not adequate in this application scenario as effects from the wireless communication channel may lead to quite variable PAoI measures for farther away vehicles – even though they play a less important role in many ITS applications.

In this paper, we proposed a new way of interpreting the AoI for arriving packets. We focus on the location of the transmitting vehicle as a metric to assess the importance of the information. Using a weighting coefficient applied to the PAoI and also to an AoI requirement, we can add a priority measure. As an example for ITS, we use the orientation and the distance of the corresponding vehicles for this process. It should be noted that the underlying PAoI metric is not changed in this procedure, i.e., compatibility with other approach is maintained. Our resulting spatial model allows to focus on timely updates of relevant vehicles for meeting a given AoI requirement, which helps saving resources on the wireless channel.

In future work, we plan further evaluation of our proposed spatial model with respect to the model parameters. Introducing our spatial model in different ITS applications can give further insights to the advantages but also limits of the AoI metric in general. The weighted PAoI and target AoI could also be used to design new classes of communication protocols, e.g., by adaptively adjusting the beacon rate based on the importance of the information to other vehicles.

6 ACKNOWLEDGEMENTS

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