

# Context-based Pseudonym Changing Scheme for Vehicular Adhoc Networks

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**Abstract**—Vehicular adhoc networks allow vehicles to share their information for safety and traffic efficiency. However, sharing information may threaten the driver privacy because it includes spatiotemporal information and is broadcast publicly and periodically. In this paper<sup>1</sup>, we propose a context-adaptive pseudonym changing scheme which lets a vehicle decide autonomously when to change its pseudonym and how long it should remain silent to ensure unlinkability. This scheme adapts dynamically based on the density of the surrounding traffic and the user privacy preferences. We employ a multi-target tracking algorithm to measure privacy in terms of traceability in realistic vehicle traces. We use Monte Carlo analysis to estimate the quality of service (QoS) of a forward collision warning application when vehicles apply this scheme. According to the experimental results, the proposed scheme provides a better compromise between traceability and QoS than a random silent period scheme.

**Keywords**-context-adaptive privacy; safety application; forward collision warning; random silent period;

## I. INTRODUCTION

Vehicular adhoc networks (VANET) are those networks formed among vehicles and roadside units (RSUs) to provide diverse traffic-related and infotainment applications. VANET are envisioned to enhance traffic safety and efficiency by increasing the awareness of vehicles about their surrounding traffic. To attain this awareness in real-time, vehicles are required to broadcast periodically their current state (position, speed, heading, etc.) in authenticated *beacon* messages. These messages may threaten the driver location privacy when they are collected by an external eavesdropper because vehicle trajectories can be reconstructed from these messages. Subsequent beacon messages are linkable whether through matching similar identifiers (i.e., pseudonyms) and tracking the subsequent spatiotemporal information [2]–[4]. Although the exchanged beacons contain no identifying information, a de-anonymization of the reconstructed anonymous traces is achievable using work/home pairs [5] or top N locations [6] and with the help of geosocial networks [7].

There are many pseudonym changing schemes (i.e., privacy schemes) proposed in literature that address this linkability issue. The main stream of these schemes suggests to preload vehicles with a pool of pseudonyms where a single

pseudonym is used at a time and changed periodically [8]. However, in order to be effective, a vehicle must change its pseudonym simultaneously with other nearby vehicles since a sole change within an area can be easily linked to the old pseudonym. Although simultaneous pseudonym changes are required, they are not sufficient to guarantee unlinkability. An adversary can utilize the spatiotemporal information to relink messages of new and old pseudonyms originating from the same vehicle using multi-target tracking techniques [3], [4].

Therefore, it is required to change pseudonyms in an unobserved zone in which the adversary cannot monitor the vehicle movements. This zone is often realized by a silent period [9] or in a predetermined location (i.e., mix-zone) [10]. On the one hand, the silent period scheme lets a vehicle stop sending messages for a random period before changing its pseudonym. After this period, the vehicle resumes broadcasting beacon messages with a new pseudonym. When the silent period is sufficiently long and several vehicles were simultaneously silent, an adversary cannot link old and new pseudonyms of each vehicle. However, long silent periods negatively affect the accuracy of safety applications. On the other hand, Freudiger *et al.* [10] proposed placing cryptographic mix-zones (CMIX) in road intersections where pseudonyms are forced to be changed in these regions. When passing by a mix-zone, vehicles obtain a symmetric key from the RSU and encrypt all messages exchanged within this zone. However, the mix-zone suffer from several shortcomings due to its fixed placement. Firstly, its effectiveness depends on the number of vehicles that enters the zone and changes their pseudonyms. Secondly, mix-zones are prone to timing and transition attacks where the adversary has knowledge of the probabilities of the exit direction and the time spent within the zone for each entering vehicle. Although these attacks can reduce the effectiveness of the mix-zone significantly, several works considered this problem such as [11]. Thirdly, mix-zones are basically depending on RSUs in its operations, although it is not expected that RSUs will be widely spread in the initial deployment of VANET.

In this paper, we propose a context-adaptive privacy scheme (CADS) that utilizes silent periods to deliver un-

<sup>1</sup>This paper is an extended version of a previous publication [1].

linkability among subsequent pseudonyms. This scheme is a significant improvement of our recent work, context-aware privacy scheme (CAPS) [12]. The CAPS allows a vehicle to monitor its context and choose when to switch to silence and change the pseudonym. Additionally, the CADS allows the driver to choose her privacy preference whether low, normal or high levels. It optimizes the internal parameters dynamically according to the density of the surrounding traffic and the driver’s privacy preference. It also preserves the vehicle pseudonyms pool for a longer time if the pseudonym is already changed with a probable confusion. Our contributions in this paper can be summarized as follows:

- Propose a context-adaptive and user-centric privacy scheme for VANET (CADS)
- Evaluate the gained privacy of CADS against both passive and active adversaries using a well-defined traceability-based metric.
- Evaluate the quality of service (QoS) of forward collision warning (FCW) application when applying the CADS.

The rest of the paper is organized as follows. We discuss related work in Section II. In Section III, we describe the system and adversary models, explain how the privacy and the quality of service of a FCW application are evaluated, and present the vehicle traces. We explain CAPS briefly in Section IV while we propose and evaluate CADS in Section V. Finally, we show conclusions and future work in Section VI.

## II. RELATED WORK

On the one hand, preserving location privacy gained a significant attention in the past decade. The silent period scheme was first proposed by Huang *et al.* [13] and applied in VANET by Sampigethaya *et al.* [9]. Li *et al.* [14] proposed Swing and Swap schemes for wireless networks that are based on silent period. In Swing scheme, a node changes its identifier and enters silence only when changing its speed and direction and there is at least one nearby node. The node broadcasts an update message to inform its neighbors which may initiate an update process if their privacy is less than the desired. In Swap scheme, nodes can exchange their identifiers with probability 0.5 after informing the authentication server. Furthermore, Gerlach and Guttler [15] propose the concept of *mix context* in VANET where a vehicle changes its pseudonym if there are N neighbors within a small distance after maintaining the pseudonym for stable time. The vehicle assesses the situation after each change to ensure the change was successful by measuring if other vehicles changed their pseudonyms in the same time step. If this is not the case, the change cycle is repeated. Buttyán *et al.* [16] propose to stop sending messages when the vehicle speed drops to low speeds, for example at intersections. The idea behind choosing low speed is that fatal accidents are

less likely to occur at low speed and places like intersections are natural mix areas where many vehicles are located in close proximity. Wei and Chen [17] propose to obfuscate position, speed and heading of vehicle within the radius of safe distance calculated by safety analysis algorithm. They also propose changing the length of the silent period based on the distance from other vehicles. Thus, the closer the vehicles are to one each other, the shorter the silent period.

On the other hand, Calandriello *et al.* [18] were one of the first to measuring the impact of changing pseudonyms on safety. They evaluated the reception timing of the new pseudonym at several distances and relative speeds. Lefevre *et al.* [19] analyzed the influence of the duration of silent period on the effectiveness of intersection collision avoidance (ICA) systems. They proposed an ICA system and evaluated a silent period scheme in terms of missed and avoided collisions. They claim that the ICA system can function well with silent periods of less than two seconds.

Our proposed scheme is inspired by but more advanced than the previously mentioned techniques. Firstly, CADS does not rely on fixed heuristics, such as a changing velocity [16] or a density threshold [15], to identify the adequate mix context to change pseudonyms. The dynamic context-based technique of CADS allows short but efficient silence periods so that the quality of safety applications is not significantly affected and also conserves pseudonyms when vehicle privacy is probably preserved. Secondly, CADS considers the driver preferences regarding privacy so that it can maximize the privacy level when the driver goes to a sensitive place. Thirdly, we employed traceability as a privacy metric rather than the size of anonymity set or entropy. The traceability metric expresses on the correctness of an adversary to reconstruct vehicle traces from beacons. The uncertainty-based metrics, such as entropy, mis-estimate the location privacy of users, as shown by Shokri *et al.* [20]. Fourthly, we considered the trade-off between privacy and safety by measuring the QoS of a FCW application. Last but not least, we employed realistic large-scale vehicle traces along with a robust vehicle tracker based on multi-target tracking technique in evaluation which confirms the scheme practicability, applicability and scalability in real-world situations.

## III. METHODOLOGY

### A. System Model

We assume each vehicle is equipped with an on board unit (OBU) which it uses to communicate with other vehicles and broadcast *beacon* messages periodically (1-10 Hz). The beacon information includes a pseudonym, a timestamp and the current vehicle state (i.e., position, speed and heading). Vehicles use a state-of-the-art pseudonym issuing process such as [21] to retrieve a pool of pseudonyms to be used one by one in the V2X communication. Pseudonyms have a *minimum pseudonym time* during which they must be kept

unchanged to ensure stable communication. After that time, a vehicle changes the pseudonym according to the adopted privacy scheme. The European standard ETSI TS 102 867 recommends changing a pseudonym every five minutes [22] while the American SAE J2735 standard recommends changing it every 120 s or 1 km, whichever comes last [23]. Since beacons are essentially used by safety applications, the broadcast information has to be as precise as possible. Thus, we assume each vehicle is equipped with a GPS receiver and combines the obtained measurements with its internal sensors to minimize the position error up to 50 cm. This small error is recommended in [24] and also realized in systems such as [25] to be able to achieve useful Cooperative Collision Warning applications (CCW). We assume that a vehicle maintains the states of its nearby vehicles located within its communication range (e.g., 300 m) using a multi-target tracking (MTT) algorithm. The utilization of a MTT algorithm for neighbor states maintenance is two-fold. First, it allows a vehicle to predict, with the help of a Kalman filter, the state of neighbors even if their beacons are delayed or missed due to a communication error or a silence period. As a result, the MTT algorithm can enhance the effectiveness of safety applications. Second, the MTT algorithm supports the vehicle in choosing the appropriate situation to change pseudonyms that increases the likelihood of tracker confusion, as will be explained in Sections IV and V.

### B. Adversary Model

We concern protecting vehicles from both (i) a global passive adversary (GPA) and (ii) a local active adversary (LAA). The GPA deploys low-cost receivers over a large part of the road network and eavesdrops on all exchanged messages. Having an external adversary that can cover the whole network may seem challenging, but we assume the worst case scenario. Also, this model is realizable, for example, by an untrusted service provider through its deployed roadside units. The main objective of the adversary is a *tracking attack* or reconstructing all vehicle traces from their beacon messages. Thus, we assume that the driver's location privacy is determined by the protection level against this attack. Although breaching the driver's location privacy requires de-anonymization of the reconstructed traces, the de-anonymization process is out of the paper scope. However, we assume that the more complete and correct the reconstructed traces, the more successful the de-anonymization process.

The adversary achieves its objective by correlating the beacons of a vehicle by pseudonym matching. When a vehicle changes its pseudonym, the adversary uses a multi-target tracking algorithm, such as NNPD [26], to correlate the messages of the old and new pseudonyms. If the adversary covers only a small part of the road network, it can still track vehicles within this limited area, but such tracking

may not be valuable regarding de-anonymization as it does not reflect complete traces. Although powerful adversaries can track vehicles using already-deployed cameras spread over the road network, the cost and inefficiency of global camera-based attacks will be much higher than those for global beacon-based attacks [10].

The LAA can send authenticated messages to the network through a limited amount of compromised vehicles driving in the road network. It is assumed that it is extremely difficult for an active adversary to be global. The LAA aims mainly to deplete the pseudonym pools of the victim vehicles by forcing repeated pseudonym changes. If its pool is depleted, the victim will attempt to refill its pseudonym pool by initiating a pseudonyms issuing process with a trusted service provider, which is not always accessible. This adversary tries to mimic conditions that make its surrounding vehicles change their pseudonyms by exploiting the procedures of the privacy scheme. Since our proposed scheme depends on the vehicle context to change the pseudonym, it is important to evaluate active internal adversaries. The encryption-based privacy schemes (such as CMIX [10]) fails in protecting vehicles from this adversary model because the compromised vehicles can obtain symmetric keys from RSUs and decrypt all exchanged messages. This gives another advantage for our proposed scheme.

### C. Privacy Evaluation

In privacy evaluation, we use the vehicle tracker proposed in [3], [26] to measure the traceability of vehicles. However, we tuned this tracker to accommodate silent periods used by privacy schemes. Originally, the tracker holds a vehicle track without update until *time-to-live* time steps and deletes it after that time from its tracks list. We included an additional parameter of the maximum silence period (*max-silence*) allowed by a privacy scheme. The tuned tracker only marks a vehicle track as inactive after *time-to-live* time steps and keeps it for additional *max-silence* time steps. When the tracker assigns messages of unmatched pseudonyms to its tracks list, only inactive tracks are considered. This modification increases the traceability of the tracker since it eliminates matching messages of new pseudonyms with unrelated tracks.

When evaluating a privacy scheme, we alter vehicle traces according to the operations of this scheme to generate pseudonymous beacons. To avoid synchronization among vehicles, they enter the road network with a pseudonym of a random life time ranges from one second up to the minimum pseudonym time. The pseudonymous beacons are provided to the tuned tracker to measure the vehicle *traceability*.

We explain the traceability metric more thoroughly since comparing the reconstructed tracks with the original vehicle traces is not trivial, as illustrated in Figure 1. In this example, there are three traces V1, V2 and V3 (drawn as solid lines on the left) that are reconstructed into three tracks T1, T2

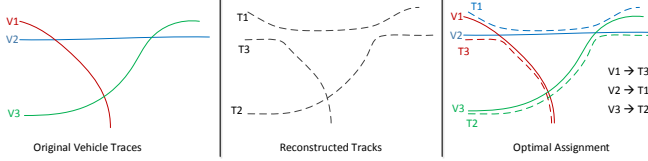


Figure 1. Traceability metric illustration

and T3 (drawn as dashed lines on the middle). By visually comparing both sets, it is clear that each track is reconstructed from partial segments of the original traces. For example, T1 is reconstructed from segments of V1, V2 and V3. Most of traceability metrics proposed in literature [13], [27], [28] may fail to reflect the actual traceability level of this adversary. The main issue of their operation is that they assign tracks to vehicle traces during the tracking process. In other words, they assume the track firstly assigned to a vehicle trace should continue with this trace till its end. However, this early assignment underestimates the length of the reconstructed tracks. For example, if the traceability of V1 is measured by assigning T1 to V1, then this metric shows a very short tracking time, although V1 is reasonably reconstructed by T3. Therefore, it will be more effective if tracks are assigned to the vehicle traces globally after the tracking process is complete.

The track-to-trace assignment is basically a nonlinear *assignment problem* where the total benefit should be maximized. The benefit represents the tracking period when a track  $t$  assigned to a vehicle trace  $v$  continuously. Let  $l(v, t), \forall v, t \in V, T$  be the maximum continuous tracking period when the track  $t$  is assigned to the vehicle trace  $v$ . Note that  $t$  can be assigned to  $v$  for disconnected segments at different times. In this case,  $l(v, t)$  represents the longest segment. The disconnected segments are not summed together because the tracking is discontinued and the track may be assigned to another vehicle trace during this discontinuity. The adversary cannot reconnect these segments and filter out this wrong assignment period because the adversary does not know if he is confused or not. Let  $\tau_v$  be the maximal tracking period of  $v$ ; and it can be obtained by solving the following assignment problem:

$$\begin{aligned}
 & \text{maximize } \sum_{v \in V} \tau_v \\
 & \text{subject to } \tau_v = \sum_{t \in T} l(v, t) \cdot a_{v,t}, \quad a_{v,t} \in \{0, 1\}, \quad (1) \\
 & \sum_{v \in V} a_{v,t} \leq 1 \quad \forall t \in T \quad \text{and} \\
 & \sum_{t \in T} a_{v,t} \leq 1 \quad \forall v \in V.
 \end{aligned}$$

Here,  $a_{v,t}$  is the assignment function which equals one if the track  $t$  should be assigned to the vehicle trace  $v$  and equals zero otherwise. Note that not all tracks must be assigned

to a vehicle trace because the number of tracks can be greater than the number of vehicle traces as some tracks are reconstructed from partial vehicle traces. Also, not all vehicle traces must be assigned to a track because its  $l(v, t)$  may not contribute to the maximal  $\sum_{v \in V} \tau_v$ . In this case,  $\tau_v$  equals zero. This assignment problem is solved using an auction algorithm considering tracks as the bidders, vehicle traces as the items and  $l(v, t)$  as the bidding price. After the optimal assignment is obtained, the traceability of the whole scenario is calculated by counting the percentage of significantly tracked vehicles. Thus, the traceability metric  $\Pi$  is defined as:

$$\Pi = \frac{1}{N} \sum_{v \in V} \lambda_v \times 100, \quad \lambda_v = \begin{cases} 1 & \frac{\tau_v}{L(v)} \geq 0.90 \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

where  $L(v)$  is the lifetime of  $v$  and  $N$  is the total number of traces included in the dataset. This metric allows few confusions around the endpoints of a vehicle trace (10% of the trace lifetime) since inaccuracies in endpoints can be smoothed by a clustering technique in a re-identification process, as shown in [29]. According to this definition, the privacy of the driver is considered breached if the adversary is able to continuously track 90% of her trace. Also, this metric reflects the probability of being tracked by calculating the ratio of tracked vehicles rather than how long a tracker can estimate from the actual trace as in [3], [4].

In some cases, some vehicles never change their pseudonyms during their lifetime. Thus, we additionally calculate the *normalized traceability*  $\Pi_n$  by excluding these vehicles since they are easily tracked by the adversary and reflected in the original traceability metric. This normalized metric considers the effectiveness of the privacy scheme when a vehicle changes its pseudonym at least once and can be defined as:

$$\begin{aligned}
 & \Pi_n = \frac{1}{N} \sum_{v \in V} \lambda_v^{norm} \times 100, \quad (3) \\
 & \lambda_v^{norm} = \begin{cases} 1 & \frac{\tau_v}{L(v)} \geq 0.90 \wedge psd(v, k_0) \neq psd(v, k_0 + L(v)) \\ 0 & \text{otherwise} \end{cases} \quad (4)
 \end{aligned}$$

where  $psd(v, k_0)$  and  $psd(v, k_0 + L(v))$  are the pseudonyms of the vehicle  $v$  at the first and last time steps in its lifetime, respectively.

#### D. Quality of Safety Application

It is important to evaluate the impact of a privacy scheme on safety applications because these applications require accurate and continuous information about nearby vehicles but, in the same time, privacy schemes usually perturb such information. We use our methodology proposed in [30] to evaluate the impact of a privacy scheme on a forward collision warning (FCW) application. In this method, vehicles estimate the states of the nearby vehicles when

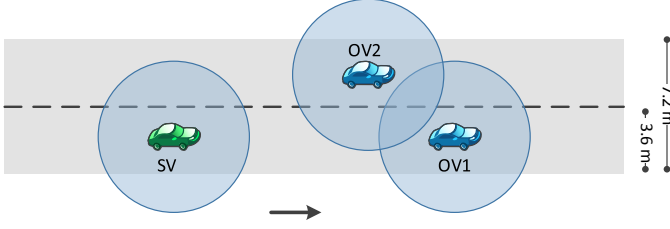


Figure 2. Forward collision warning scenario.

applying the evaluated privacy scheme and calculate the error  $\delta$  between their estimation and the ground truth. Then, the probability of correctly calculating the main application factors is estimated using these error samples in Monte Carlo analysis. The main factors of the FCW application are (1) identifying the correct lane of the other vehicle and (2) calculating the time to collision (TTC) accurately within small tolerance (e.g., within 500 ms).

For the first application requirement, the SV must correctly identify that OV1 is in its own path (i.e., high sensitivity) while OV2 is not (i.e., high specificity), as shown in Figure 2. The criteria for identifying an OV as in path is that its lateral position is within  $\pm 1.8$  m of the lateral position of the SV, assuming a 3.6 m lane width. Otherwise, it should be identified as not in path. In our analysis, we set the true lateral position of the SV as same as the lateral position of OV1, while the true position of the OV2 is located in the center of the next lane. Thus, the measured lateral positions  $y$  of SV, OV1 and OV2 are obtained by adding the errors to their true positions as follows:

$$\begin{aligned} y_{SV} &= 1.8 + \mathcal{N}(0, 0.5) \\ y_{OV1} &= 1.8 + \delta y \\ y_{OV2} &= 5.4 + \delta y \end{aligned} \quad (5)$$

where  $\delta y$  is an error sample in the lateral position. Therefore, the true and false positive probabilities for correctly identifying lanes of the OVs can be calculated by:

$$P_{true+} = P(|y_{OV1} - y_{SV}| \leq 1.8) \quad (6)$$

$$P_{false+} = P(|y_{OV2} - y_{SV}| \leq 1.8) \quad (7)$$

For the second requirement, we assume that the SV is approaching the OV1 at speed differences  $\Delta s$  of 5 m/s and 15 m/s. The assumed true TTC is set to three seconds as an example; thus, the true position of OV1 is generated to be three seconds distance from the true position of SV and is calculated based on the evaluated speed difference as follows:

$$\begin{aligned} x_{SV} &= \mathcal{N}(0, 0.5) \\ x_{OV1} &= 3 \cdot \Delta s + \delta x \\ \dot{x}_{SV} &= \hat{x}_{OV1} + \Delta s + \mathcal{N}(0, 0.02 \cdot (\hat{x}_{OV1} + \Delta s)) \\ \dot{x}_{OV1} &= \hat{x}_{OV1} + \delta \dot{x} \end{aligned} \quad (8)$$

where  $\hat{x}_{OV1}$  is the true longitudinal speed of the OV1 and  $\delta \dot{x}$  is an error sample in the longitudinal speed. Here, there is no binary classification to calculate false positives; instead, we calculate the probability of calculating TTC within a small tolerance of 500 ms. This 500 ms tolerance is chosen by Shladover and Tan [24] as the maximum tolerance for issuing a useful warning. They also analyzed the implication of a desirable tolerance of 200 ms but they found that it requires a positioning accuracy of 20 cm to attain this restrict tolerance, wherefore we considered only the maximum tolerance of 500 ms. Therefore, the TTC and the probability of correctly estimating it within 500 ms can be calculated by:

$$TTC = \frac{x_{OV1} - x_{SV}}{\dot{x}_{SV} - \dot{x}_{OV1}} \quad (9)$$

$$P_{TTC} = P(|TTC - 3| \leq 0.5) \quad (10)$$

In this equation, we determine how frequently the difference between the calculated TTC and the true TTC (3 s) is less than the tolerance threshold of 0.5 s. Finally, the probability of the FCW application ( $P_{FCW}$ ) can be obtained by multiplying all three probabilities together, assuming they are independent, as follows:

$$P_{FCW\Delta s} = P_{true+} \times (1 - P_{false+}) \times P_{TTC\Delta s} \quad (11)$$

Experiments show that estimating TTC in high speed differences is much more accurate than low speed differences with the same position noise. Therefore, the QoS of the FCW application ( $QoS_{FCW}$ ) is defined as  $P_{FCW\Delta s=5}$  multiplied by 100 to obtain a percentage, as follows:

$$QoS_{FCW} = P_{FCW\Delta s=5} \times 100 \quad (12)$$

### E. Vehicle Traces

We employ realistic vehicle traces in evaluation which are obtained from [31]. This dataset is mainly based on the data made available by the TAPASCologne project [32] which is an initiative by the Institute of Transportation Systems at the German Aerospace Center (ITS-DLR). This dataset reproduces vehicle traffic in the greater urban area of the city of Cologne, Germany with the highest level of realism possible. The street layout of the Cologne urban area is obtained from the OpenStreetMap (OSM) database. The microscopic mobility of vehicles is simulated using the Simulation of Urban Mobility (SUMO). The source and destination of vehicle traces are derived through the Travel and Activity PAtterns Simulation (TAPAS) methodology. Uppoor *et al.* [33] pointed out several problems when combining these data sources to produce traffic data. Among these problems, vehicles are moving rapidly to large traffic jams, travel times are unrealistic and vehicle speeds turn to very low values. Uppoor *et al.* resolved these problems so that the synthetic traffic match that observed in the real world, through real-time traffic information services. This is why we name this dataset as realistic traces.

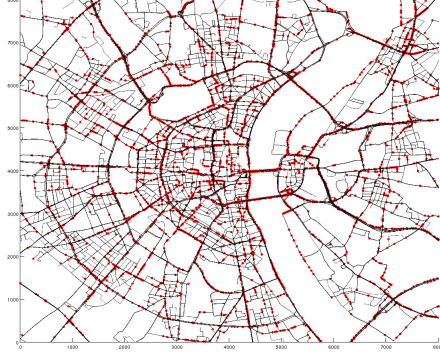


Figure 3. The road map of the realistic traces.

We obtained the two-hour sample published online [31] and selected 30 min (from 6:15 AM till 6:45 AM) for the middle  $64 \text{ km}^2$  region, as shown in Figure 3. We selected this time period because the vehicle density increases dramatically, which provides a challenging evaluation for the operation of privacy scheme in different densities. As we cropped the vehicle traces in both space and time, we excluded very short traces that move within  $100 \text{ m}^2$  or start and end in less than 15 s. There are 19,704 remaining traces with increasing density, ranging from 1,929 to 4,572 simultaneous vehicles in the first and last time steps, respectively. The vehicle positions in the last time step are drawn as red spots in Figure 3. Moreover, we processed the dataset to calculate the heading and velocity in the  $xy$ -coordinates using every two consecutive time steps for each vehicle. The last heading value is preserved when the vehicle stops and is changed when it starts to move.

#### IV. CONTEXT-AWARE PRIVACY SCHEME (CAPS)

The basic concept of our Context-aware Privacy Scheme (CAPS) is to determine the appropriate context in which a vehicle should change its pseudonym. This approach aims to increase the effectiveness of such changes against tracking and avoid wasting pseudonyms in easily traceable situations. More specifically, a vehicle continuously monitors other vehicles located within its communication range and tracks their beacons using an NNPD algorithm. As explained in our work [26], the NNPD is an efficient multi-target tracking algorithm that has exhibited a high tracking accuracy for anonymous beacons with different amounts of noise and beaconing rates.

As illustrated in Figure 4, the CAPS works as follows. During its active status, the subject vehicle (SV) uses its current pseudonym in beacons until the pseudonym lifetime reaches a minimum time. Once it exceeds this time, the vehicle checks whether any of monitored *neighbors* missed its beacons for several time steps. Here, neighbors refer to vehicles located within a predefined radius from the subject vehicle (e.g., 50 or 100 m). If the SV finds a silent neighbor, it turns to silence as well. Otherwise, it continues using

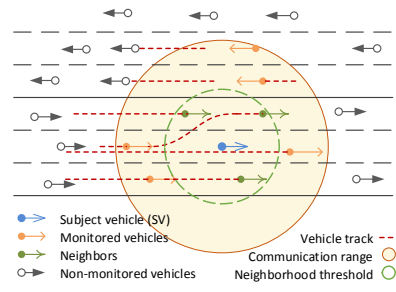


Figure 4. Illustration for the CAPS operations

its current pseudonym until its lifetime reaches a maximum pseudonym time and then the vehicle turns to silence.

When a vehicle is silent, it returns to beaconing under more complex conditions based on the *gating* phase of vehicle tracking. It was explained in [26] that a gating process is required in target tracking to eliminate unlikely measurement-to-track associations from being tested. It requires any new measurement to be located within the track *gate* to be a valid candidate for association with this track. The most common gating technique is ellipsoidal which defines the norm of the residual vector ( $d^2$ ):

$$d^2 = \tilde{z}^T S^{-1} \tilde{z} \quad (13)$$

where  $\tilde{z}$  and  $S$  are the residual vector and its covariance matrix obtained from the Kalman filter, respectively. We exploit this fact and require the beacon after silence to achieve one of the following two conditions to guarantee no correlation with previous beacons. As illustrated in Figure 5, the SV state should be nearer to the track of a silent neighbor than its original track or completely outside the gate of its original track. When these conditions hold, the adversary will most probably become confused when attempting to correlate this new beacon because it will not be assigned to its original track.

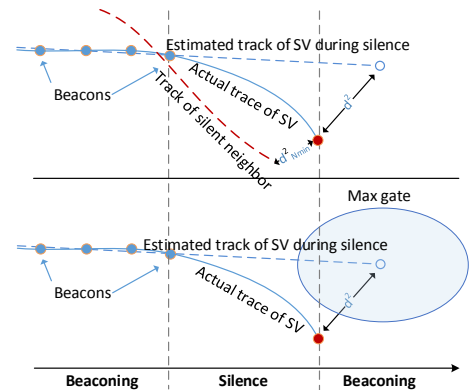


Figure 5. Illustration for the two conditions to exit silence.

Formally, when the SV is silent, it continues monitoring surrounding vehicles and waits for the minimum silence



time. Once exceeded, it checks if one of the following conditions holds regarding the norm of the residual vector ( $d^2$ ) between its actual and estimated states:

- 1)  $d^2 > d_{Nmin}^2$ , where  $d_{Nmin}^2$  is the minimum norm of the residual vector between the SV actual state and the estimated states of its silent neighbors, as shown in the upper part of Figure 5.
- 2)  $d^2 > max\_gate$ , where  $max\_gate$  is the maximum gate that the adversary may use, as shown in the lower part of Figure 5.

If one of these conditions holds, this new beacon is likely to be mixed with one of its silent neighbors or recognized as a new vehicle. Therefore, it is a suitable time to exit silence with a new pseudonym. If these conditions never occur, the SV remains silent until a maximum silence time is reached.

#### A. CAPS Evaluation

We evaluate the CAPS in comparison with two silent-based schemes: the random and coordinated silent period schemes. The random silent period (RSP) allows a vehicle to change its pseudonym after a fixed pseudonym time and keep silent for a uniformly random period within a preset range (e.g., from 3 to 13 s). As the two schemes have different assumptions and parameters, they are aligned based on the median silent and pseudonym times for all vehicles, actually performed in the simulation. The maximum pseudonym time of CAPS is 300 s while the fixed pseudonym time of RSP is 120 s. In CAPS, we assigned 50 m to the neighborhood threshold and 60 s to the minimum pseudonym time. The coordinated silent period (CSP) is proposed by Tomandl *et al.* [34] in their comparison of silent period and mix zone schemes. CSP coordinates all vehicles in the network to remain silent and change pseudonyms synchronously. CSP seems to be theoretical since the coordination overhead in real world situations increases dramatically [34]. However, CSP increases the privacy significantly because it maximizes the size of the anonymity set at every pseudonym change. The pseudonym lifetime of CSP is 300 s and all vehicles are synchronized so that they turn to silence and change pseudonyms simultaneously.

In Figure 6, we show the traceability  $\Pi$ , normalized traceability  $\Pi_n$  and QoS of a FCW application for all schemes. The CAPS slightly reduces the traceability  $\Pi$  especially in short median silence times (up to 10% lower than RSP) as shown in Figure 6(a). In longer silent times, all schemes result in similar traceability. Since many vehicles did not change their pseudonyms in simulation, CAPS and CSP reduced the normalized traceability by up to 20% and 30% from the traceability metric, respectively. This happens because the CAPS chooses the right context to change the pseudonym which increases the probability of tracker confusion. Hence, the pseudonym change made by the CAPS is much more effective than that made randomly by the RSP. For CSP, vehicles are synchronized which maximizes the

size of the anonymity set and increases the tracker confusion significantly.

For the QoS, the CAPS achieves a higher QoS than the RSP (up to 6% higher) and slightly lower than CSP (up to 2% lower). This QoS decrease in the RSP occurs due to the unnecessary and ineffective pseudonym changes. These pseudonym changes are followed by silence periods which affects identifying the application requirements correctly especially with relatively long silence periods.

#### B. CAPS Shortcomings

We note three shortcomings of the CAPS. First, we observe that some vehicles change pseudonyms unnecessarily several times with no significant advantage in decreasing the traceability. Having a few confusions per trace is sufficient to avoid continuous vehicle tracking. However, frequent pseudonym changes and confusions may negatively affect the QoS of a safety application, as neighbors cannot estimate the vehicle state correctly. Therefore, we propose increasing the minimum pseudonym time each time a vehicle changes its pseudonym with a probable confusion. Second, the CAPS takes several parameters that may not be optimized for different traffic densities and situations. For example, a wide neighborhood threshold may be more suitable for sparse traffic than dense traffic. Third, the CAPS does not consider the driver's preference regarding privacy. In fact, privacy depends on the preferences of the user and the technical solutions should be adaptable to empower users to determine what is allowed with their personal information [35]. For example, it may be desirable to maximize the privacy level when the driver goes to a sensitive place. For these reasons, we propose a more advanced scheme that considers these shortcomings, which we call the context-adaptive privacy scheme (CADS) as explained next.

### V. CONTEXT-ADAPTIVE PRIVACY SCHEME (CADS)

The CADS allows a driver to choose among privacy preferences, whether low, normal or high. It optimizes the internal parameters dynamically according to the density of the surrounding traffic and the driver's privacy preference. In addition, it preserves the vehicle pseudonyms pool for a longer time if the pseudonym is already changed with a probable confusion.

To optimize the scheme parameters with respect to the surrounding traffic, we investigate the performance of the CAPS in two different densities; sparse and dense traffic. First, we select two relatively short sub-datasets from the realistic vehicle traces with low and high traffic densities. We then test the CAPS on each sub-dataset with many parameter combinations and obtain the resulting traceability and QoS metrics. Second, to incorporate the privacy preference in CADS, we divide the results of the sub-dataset experiments into three categories according to the achievable traceability. Next, we identify the parameters that result in the best

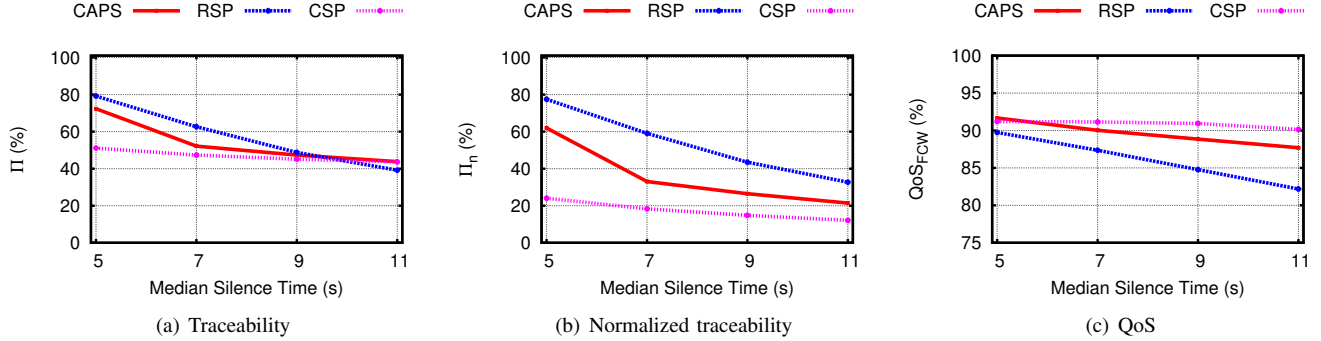


Figure 6. Evaluation comparison among CAPS, RSP and CSP.

Table I  
OPTIMIZED CADS PARAMETERS AND THEIR RESULTS

Parameter/Result	Privacy Preference					
	Sparse sub-dataset			Dense sub-dataset		
	Low	Normal	High	Low	Normal	High
Max pseudonym time (s)	240	300	180	240	180	180
Max silence time (s)	11	11	11	11	13	11
Pseudonym time increment (s)	60	60	0	60	60	0
Neighborhood threshold (m)	50	100	100	50	50	100
Traceability (%)	75	59	49	68	49	38
Normalized Traceability (%)	52	33	31	43	26	21
QoS (%)	90	87	85	91	88	85

compromise between traceability and QoS in each category. Third, we insert these categorized parameters of each density into CADS and bind them according to the real-time vehicle density and the input privacy preference.

#### A. Sub-datasets Evaluation

As explained in Section III-E, the vehicle traces have an increasing density ranging from 1,929 to 4,572 vehicles. We selected two sub-datasets, 6 min long each from the beginning and end of vehicle traces, as shaded in Figure 7(a). We excluded traces that last less than one minute from these sub-datasets. The CAPS is then evaluated using each sub-dataset and the following parameter combinations: maximum pseudonym times of 180, 240 and 300 s, maximum silence times of 7, 9, 11 and 13 s, neighborhood thresholds of 50 and 100 m and increments of the minimum pseudonym time after a probable confusion of 0 or 60 s. We run the CAPS using these parameter combinations on both sub-datasets and obtain the achieved privacy and QoS metrics.

#### B. Parameters Selection

From all experiments tested in the previous step, we exclude those results with a QoS less than 85% as we assume that the safety application will not operate with an acceptable accuracy in such cases. Although the traceability and the QoS are proportional, we notice that the QoS varies much less than the traceability. Therefore, the results are categorized based on the QoS instead, to facilitate categorization. The results are divided into low, normal and high

privacy levels when they achieve the maximum, average and minimum QoS, respectively in each sub-dataset. Thus, the parameters for a high privacy preference are selected when a QoS of 85% is attained. The parameters for a low privacy preference are selected when the highest QoS is obtained but with a traceability of at most 75%. This traceability constraint is added to ensure some privacy even when low privacy preference is selected. The parameters for normal privacy preference are selected when the average QoS is attained with the lowest traceability.

In Table I, we show the selected parameter set for each privacy preference and vehicle density. In the last three rows, we include the resulting traceability and QoS of each parameter set when applied to the sub-datasets. We notice that the achievable traceability in the sparse sub-dataset is higher than that achievable in the dense sub-dataset. The traceability can be decreased using more restrict parameters but only at the cost of the QoS.

#### C. CADS Algorithm

The parameter table I is integrated into the CADS to let a vehicle choose the adequate parameter set based on the driver's privacy preference and the real-time density of the surrounding traffic. A vehicle can estimate the traffic density by evaluating the average number of neighbors encountered over time. For this purpose, we analyzed the distribution of neighbors in both sub-datasets, as shown in Figure 7. We notice that the average number of neighbors that a vehicle encounters is 30 and 68 with 95% confidence in the sparse



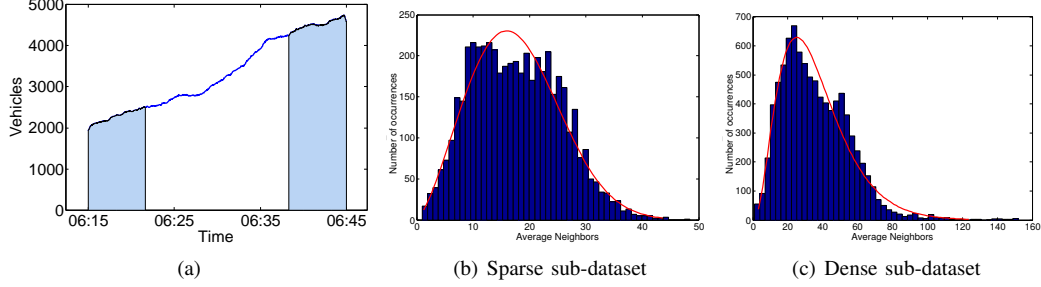


Figure 7. (a) Vehicle density versus time with sub-datasets highlighted. (b) and (c) Average number of neighbors encountered by a vehicle in each sub-dataset.

and dense sub-datasets, respectively. Therefore, a neighbors threshold of 30 vehicles is assigned to discriminate between sparse and dense traffic. In other words, a vehicle continuously counts the surrounding vehicles in its communication range and calculates the average over time. If the average number of surrounding vehicles is lower than 30 then the traffic is considered sparse, otherwise it is considered dense.

#### D. CADS Evaluation

1) *Location Privacy under GPA*: CADS was evaluated under the GPA in two different scenarios. In the first scenario, all drivers select the same privacy preference whether low, normal or high level. Figure 8 displays the traceability, the normalized traceability and the quality of service of each privacy level. As a kind of comparison, the measurements for the CAPS scheme of 11 s maximum silent time are shown as dashed lines. The traceability and normalized traceability of CADS decrease when drivers select a higher privacy preference with a slight decrease in the QoS. Compared to CAPS, the CADS achieves a better compromise between traceability and QoS. Specifically, when a high privacy preference is used, the CADS achieves a 13% lower traceability but with a slight decrease in QoS (only 4%). When a low privacy preference is used, the QoS is enhanced by 2% while the normalized traceability is still lower than 40%. In normal privacy preference, traceability is slightly decreased because of the adaptation of the parameters based on the traffic density. These results confirm the validity and effectiveness of the context-adaptability to find a practical compromise between privacy preference and QoS.

In the second scenario, we allow vehicles to select the preferred privacy level randomly based on given percentages. In this scenario, we aim to confirm that the privacy is more enhanced for vehicles that select a higher privacy level than the others. As the vehicles use a mix of privacy preferences, each privacy preference group is evaluated separately showing its traceability and normalized traceability. However, the QoS is evaluated over all vehicles, as lower-quality information obtained from vehicles that use a high privacy preference will affect other vehicles of lower privacy preferences and vice versa. In this scenario, we repeat each

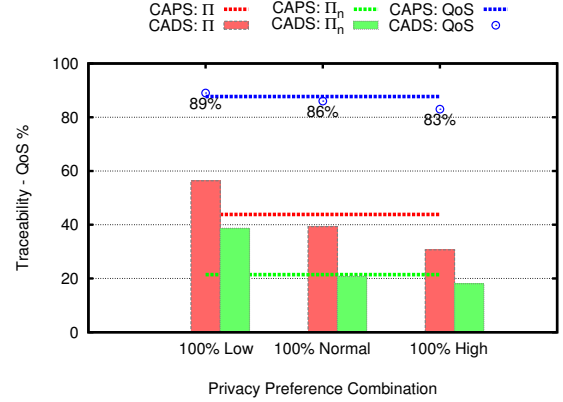


Figure 8. The CADS evaluation when all vehicles use the same privacy preference compared to the CAPS of 11 s max silent time.

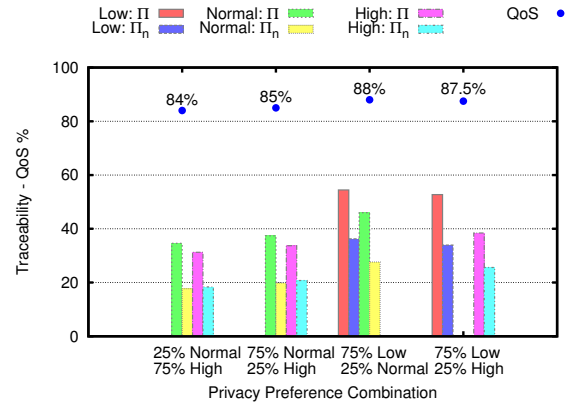


Figure 9. The CADS evaluation when vehicles use a random privacy preference based on the specified percentages.

experiment five times with random selection of the privacy preference assigned to vehicles.

In the first and second experiments, 25% and 75% of vehicles use the normal privacy preference, respectively, while the rest uses the high privacy preference, as shown in Figure 9. Although both experiments employ swapped percentages of normal and high privacy levels, they achieve similar (normalized) traceability for both level groups with

Table II  
CADS RESULTS UNDER THE LAA PSEUDONYM DEPLETION ATTACK IN  
SPARSE SUB-DATASET (SILENT NEIGHBOR THRESHOLD = 1; 3967  
VEHICLES)

	No LAA	LAA strength			
		1%	3%	5%	10%
Compromised vehicles	0	40	119	198	397
Concerned vehicles (victim)	2106	224	557	1041	1562
Avg. pseudonym lifetime (s)	114	88	85	80	74
Pseudonym change/Vehicle	1.3	1.8	1.8	1.8	1.9
$\Pi_n$ (%)	37	24	21	24	25
QoS (%)	88	87	85	83	79

slight effect of the major group on the performance of the minor group.

In the third and fourth experiments, 75% of vehicles use the low privacy preference while the rest use normal and high levels, respectively. It is observable that the high level group in the fourth experiment achieves a lower traceability than that is achieved by the normal level group in the third experiment. Additionally, we notice that the high level group in the fourth experiment achieves slightly higher traceability than the same group in the second experiment. This result may attributed to the major privacy preference group being low-level in the fourth experiment but normal-level in the second. Regarding the QoS, we notice that it follows the QoS of the major group with a slight effect from the minor. For example, the QoS in the first experiment is higher 1% than that in the “100% high-privacy” experiment, and the QoS in the fourth experiment is lower 1.5% than that in the “100% low-privacy” experiment. From all these observations, we can conclude that the traceability is mainly affected by the configured privacy level with a slight effect from the surrounding traffic. However, this change in traceability is compensated in the QoS.

2) *Location Privacy under LAA*: The local active adversary (LAA) performs a pseudonyms depletion attack which tries to force victim vehicles to change pseudonyms as soon as possible. It is important to evaluate context-based schemes under this attack because these schemes change pseudonyms based on conditions that are external from the vehicle. Therefore, an adversary may try to mimic these conditions to force vehicles change pseudonyms frequently and deplete their pseudonyms pool. We simulate this attack by letting a random number of compromised vehicles drive within the road network. These vehicles act as LAA by changing their pseudonyms every 5 s and keep silent for 3 s and so on. This behavior is challenging the practicality of this attack because if the compromised vehicles change their pseudonyms, they will suffer from self-depletion in short time when they use authenticated pseudonyms. If they use fake pseudonyms or do not change pseudonyms but switch to silence frequently, surrounding vehicles can detect this behavior and abandon the compromised vehicles from

Table III  
CADS RESULTS UNDER THE LAA PSEUDONYM DEPLETION ATTACK IN  
DENSE SUB-DATASET (SILENT NEIGHBOR THRESHOLD = 2; 7390  
VEHICLES)

	No LAA	LAA strength			
		1%	3%	5%	10%
Compromised vehicles	0	74	222	370	739
Concerned vehicles (victim)	3526	744	2015	2946	3855
Avg. pseudonym lifetime (s)	156	142	132	122	103
Pseudonym change/Vehicle	1.1	1.2	1.2	1.3	1.4
$\Pi_n$ (%)	38	30	31	30	27
QoS (%)	91	90	89	88	86

affecting their decisions. Regardless of the practicability issues, we assume here that the compromised vehicles own infinite number of authenticated pseudonyms and is able to change it freely.

In the worst case scenario, a victim vehicle will change its pseudonym every minimum pseudonym time, but the CADS can reduce the effect of this attack through its parameter: the silent neighbor threshold. When the silent neighbor threshold is set to be more than one, the scheme requires several silent neighboring vehicles to switch to silence. This condition hinders the LAA attack since it is unlikely to have several LAA vehicles neighboring the victim vehicle. Also, CADS can employ the pseudonym time increment parameter to increase the minimum pseudonym time when the pseudonym is changed with a likely tracker confusion.

The CADS is evaluated against the LAA of different strengths in terms of the number of the compromised vehicles. The protection against this attack is measured by the number of pseudonym changes and the pseudonym lifetime made by vehicles on average. When calculating this metric, we considered only vehicles that met a LAA vehicle within 50 m radius for at least 15 s and changed their pseudonyms during simulation at least once. We selected the first and the last 5 min of the realistic traces and run simulation five times for each LAA strength with different compromised vehicles selected randomly. We selected 2 sub-datasets to show the effect of LAA on both sparse and dense traffic. These short traces will not affect the generality of the obtained results because we consider the pseudonym changing behavior rather than a full reconstruction of long traces. We tested two thresholds of silent neighbors of 1 and 2 vehicles where all vehicles choose the normal privacy preference.

Table II shows the average metrics obtained using a silent neighbor threshold of one for the sparse sub-dataset. Four LAA strengths along with the case of no LAA are evaluated. The number of the compromised vehicles and the concerned vehicles, on which the given metrics are calculated, are listed in the first two rows of Table II. The concerned vehicles are those changed their pseudonyms at least once and refer to the victim vehicles when LAA is

present or all vehicles for the no LAA case. The next two rows show the average pseudonym lifetime and the number of pseudonyms changed per vehicle. It can be observed that the victim vehicles changed pseudonyms 1.38 times more than the case of no LAA. This small increase in pseudonym changes cannot result in pseudonym depletion unless the LAA vehicles continuously follow the victim vehicles. Furthermore, we show the traceability and QoS metrics for each case. Interestingly, the normalized traceability metric  $\Pi_n$  is decreased when the LAA is present because the compromised vehicles force surrounding vehicles to change pseudonyms. The increased pseudonym changes result in a decrease in QoS depending on the LAA strength. We repeated this experiment with a silent neighbor threshold of 2 but we found that the traceability is significantly increased because it is rarely to find two silent neighbors in this sparse traffic.

Table III shows the average metrics obtained using a silent neighbor threshold of 2 for the dense sub-dataset. We use here a threshold of 2 because the traffic is dense and it is common to meet with a compromised vehicle repeatedly. We observe that the victim vehicles changed pseudonyms 1.27 times more than the case of no LAA at maximum. The same behavior of decreased traceability and slight reduction in QoS is also observed.

From these observations, we conclude that a weak LAA of small percent of compromised vehicles (e.g., up to 3%) does not add a significant risk of pseudonyms depletion specially when setting the silent neighbor threshold to more than one. Also, this attack may hinder the threat of the GPA attack with a small impact on the QoS of safety applications.

#### E. CADS Efficiency

CADS was implemented using MATLAB as a centralized program, which operates on samples located in the communication range of each vehicle separately. We exploit the parallel for loop feature in MATLAB to iterate on vehicles asynchronously at every time step. We run our experiments on an Intel QuadCore i7-4800MQ @ 2.70GHz Hyper-threaded CPU. We calculate the running time of the CADS to process samples received by a vehicle in a single time step and average over all vehicles and time steps. We found that the average running time is 5 ms for realistic traces. Note that this running time is obtained using a single thread, as the CADS code is basically sequential. Thus, this running time is reproducible on single-thread single-core CPUs of the given speed. Therefore, we can conclude that the CADS is efficient when high-end CPUs are used because the most frequent beaconing rate is 100 ms and the vehicle will have plenty of time to do other tasks. However, if lower-end CPUs are used inside vehicles, then further code optimization should be investigated. The memory is not an

issue, as the CADS uses only a few hundreds of kB for the Kalman filter tracks of the nearby vehicles.

## VI. CONCLUSION

We discussed context-aware (CAPS) and context-adaptive (CADS) privacy schemes for vehicular networks. They utilize a context monitoring module to track surrounding neighbors and identify adequate situations to change pseudonym and determine the effective length of silence period. In CADS, a driver can choose the desired privacy level and the scheme can automatically identify the appropriate parameters that match this desired level based on the real-time traffic density. Based on the experimental results, CADS can reduce traceability than the CAPS does when normal or high privacy levels are selected with a slight reduction in the QoS. Also, the CADS can preserve lowest traceability for vehicles that select a high privacy level even when they drive within a majority of vehicles selected a lower privacy level. In future work, we will compare CADS with advanced privacy schemes such as mix-zones. Also, we will investigate allowing vehicles measure the safety level in real-time to stop silence in critical situations, for example. Lastly, we will consider deploying CADS on a test platform for VANET such as NEC LinkBird-MX to measure and optimize its practical efficiency.

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