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Privacy Challenges with Protecting Live Vehicular Location Context

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ABSTRACT Future Intelligent Transport Systems (ITS) will require that vehicles are equipped with Dedicated Short Range Communications (DSRC). With these DSRC capabilities, new privacy threats are emerging that can be taken advantage of by threat actors with little experience and cheap components. However, the origins of these privacy threats are not limited to the vehicle and its communications, but extend to non-vehicular devices carried by the driver and passengers. A shortcoming of existing work is that it tends to focus on a specific aspect of privacy leakage when attempting to protect location privacy. In doing so, interactions between privacy threats are not considered. In this work, we investigate the *privacy surface* of a vehicle by considering the many different ways in which location privacy can be leaked. Following this, we identify techniques to protect privacy and that it is insufficient to provide location privacy against a single threat vector. A methodology to calculate the interactions of privacy preserving techniques is used to highlight the need to consider the wider threat landscape and for techniques to collaborate to ensure location privacy is provided against multiple sources of privacy threats where possible.

INDEX TERMS Location Privacy; Connected Vehicles; Privacy Surface; Technique Interaction

I. INTRODUCTION

CONNECTED and Autonomous Vehicles (CAVs) are expected to be widely deployed on road networks globally within the next decade. Therefore, transportation networks will deploy Intelligent Transportation Systems (ITSs) to manage these vehicles. An issue with these systems is that they raise privacy concerns due to the ease in which they allow a vehicle to be tracked. However, vehicle tracking has been of interest to threat actors trying to violate privacy for some time. In the recent past, violating location privacy has only been generally available to resource rich threat actors for mass surveillance or knowledgeable threat actors that focus on individual vehicles. For example, Automatic Number Plate Recognition (ANPR) allows vehicles to be tracked en masse, but it requires a deployment of ANPR cameras over a large area that is both expensive and noticeable. Individual vehicles can be tracked by threat actors with limited resources using location recording devices, but physical access is required for installation and they may be noticed by the driver. New vehicular technologies provide methods of vehicle tracking that are cheaper, have fewer limitations, easier to deploy, and in some cases, harder to detect.

These new tracking techniques usually do not focus solely on the vehicle's location but also consider its identity and the time was detected. This can be because the threat actors are interested in who was where at specific times, or how the location of a vehicle changes over time. Location, time, and identity are types of *context* information and protecting the privacy of the context in which a vehicle performs actions is often harder than protecting against *content* privacy leaks. Content privacy can be protected using encryption, however, context privacy requires bespoke solutions for the context being protected and the different scenarios it is protected in. A privacy hierarchy is provided in Figure 1.

There are two main issues with existing work on protecting vehicular location privacy. The first is that there is a lack of positioning of the context in which location privacy is being provided. This necessary to understand which threats an adversary will take advantage of and why. In response, we propose a *privacy surface* which identifies the threat actors, their motivations, and capabilities. This landscape consists of existing threats, techniques to counter them, and a classification of both threats and techniques. In this paper, we focus on *live* privacy threats and only briefly cover *historical* threats. This is because live privacy threats can be converted into historical privacy threats by threat actors logging data. Different types of live privacy threats can be protected by the same approaches when converted to historical privacy threats, whereas the live threats themselves need to be protected in different ways.

The second issue is that existing privacy preserving techniques tend to be developed in isolation and do not consider the impact the wider threat landscape has on the implementation of the privacy preserving technique. For example, the majority of survey papers focus on specific areas, such as Location Based Services (LBSs) [1, 2, 3], instead of considering a wider range of privacy threats. Some look at privacy [4] or privacy and security [5] in general, but do not present a broad range of privacy threats.

To address this, the privacy landscape classes identified in this paper are used to predict the ways in which privacy preserving techniques will need to be adjusted to consider other simultaneous privacy threats. This is because the interactions between different privacy threats and techniques may render the privacy preserving technique for the original threat ineffective when considering additional privacy threats and techniques. For example, one highlighted area to consider is the interaction between different sources of identity (such as a vehicle's identity and the identity of devices within the vehicle) which periodically change that public identity. This identity change needs to be synchronised to prevent linking the old to new identity of one source via an unchanged identity from another source. We also identify a number other of specific cases that warrant future investigation into how to protect location privacy when multiple privacy threats interact. Future work in this area needs to consider the interactions of privacy preserving techniques, to ensure live vehicular privacy is preserved.

To summarise, the contributions of this paper are:

1) To propose a privacy surface of connected vehicles to identify the *live* privacy threats, threat actors, and the privacy preserving techniques used to provide privacy.
2) To classify the threats and techniques into common categories in order to support a generic analysis.
3) To identify potential ways in which privacy threats interact and may require changes to the privacy preserving technique when considering other privacy threats and techniques.

The remainder of this paper is structured as follows. The survey of privacy threats to a vehicle will be presented in Section II. The threat actors will be identified in Section III before the survey of privacy preserving techniques is presented in Section IV. In Section V we will analyse the impact that privacy preserving techniques have on each other, before a discussion of our work in Section VI. Section VII will present future work on this topic and this paper concludes in Section VIII.

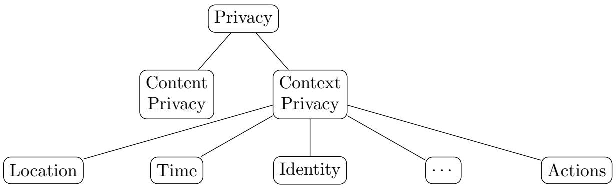

Figure 1: Privacy Hierarchy

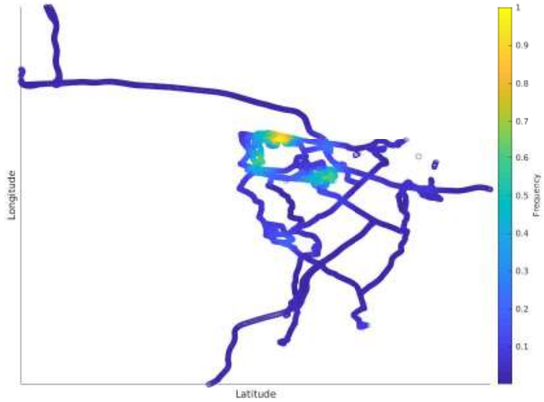

Figure 2: Heatmap of GPS trajectory collected over two weeks.

II. LOCATION PRIVACY THREATS

Modern vehicles are identifiable by more than just their appearance and licence plate numbers. This is a result of their increased complexity and functionality, provided by new technologies that enable communication with road infrastructure and other vehicles, such as Dedicated Short Range Communications (DSRC). These communication vectors provide possibilities for vehicle identification, and thus may compromise privacy. If a threat actor is able to obtain a detailed history of a vehicle's location it will be capable of creating an analysis of this data that reveals information the owner of the vehicle may wish to keep private. One potential analysis is a heatmap representing the frequency of locations where the vehicle has been. An example heatmap generated from data collected over a two week period from the same person is shown in Figure 2. In this map there are three points of interest, including their home, workplace, and a local bar, accompanied by the routes used between them. Linking even this small series of GPS trajectories to a map, it is possible to elicit the details of someone's pattern of life [6].

In this section we identify the various privacy threats through which the location privacy of a vehicle may be compromised. In Section IV the privacy preserving techniques that correspond to these threats will be presented. The

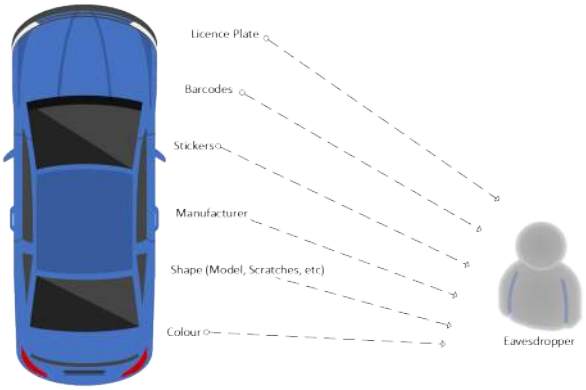

Figure 3: Some of the identifiable features of vehicle

privacy threats are classified into eight classes: (A) Direct Access to GNSS Data, (B) Visual Identification, (C) Services, (D) Internal Vehicle Communication, (E) External Vehicle Communication, (F) Non-vehicle Communication, (G) Behaviour, and (H) Historical Data. Each class has a number of different techniques that can be used to preserve privacy that will be discussed in Section IV. As threat identification is a continuous process, not all live privacy threats may be present in this categorisation.

A. DIRECT ACCESS TO GNSS DATA

One of the simplest ways in which a vehicle can be tracked is to attach a Global Navigation Satellite System (GNSS) sensor (such as GPS) to the outside of a vehicle, along with a battery and a cellular radio to report the location to a threat actor. Additional sensors, such as accelerometers can be included to improve accuracy. These devices are cheap and easy to obtain [7]. The downside is that a device needs to be attached to each vehicle that a threat actor wishes to track, which makes mass vehicle tracking infeasible.

These vehicle tracking devices may be intentionally installed by some authority. For example, a logistics firm may wish to track and manage their fleet of vehicles. Even if unintentional, it is possible that the data captured may be personal to the driver and privacy sensitive. Similarly, personal information is available by insurance companies who give preferential rates to those willing to install a black box in their vehicle [8].

B. VISUAL IDENTIFICATION

Vehicles have been partially identifiable since their inception by their colour, shape, manufacturer, and other aspects such as tyre tread (highlighted in Figure 3). Since the beginning of the 20th century it has been mandatory to have an identifying number plate attached to the vehicle. The UK passed the Motor Car Act 1903 [9, §2(1–2)], making unique licence plates mandatory in 1904, around the same time some states in the USA also introduced them. Since then, it has been possible to identify a vehicle upon inspection of the series of letters and numbers attached to it. With the advent of Automatic Number Plate Recognition (ANPR) [10], this identification was automated and widespread tracking of vehicles became possible.

ANPR operates by first finding number plates in an image and processing it to allow optical character recognition to identify the symbols attached to the vehicle. Due to inexpensive image recording equipment and the development of reliable image processing algorithms, ANPR is now used by law enforcement throughout the world. It is also used in many other scenarios, such as on toll roads and bridges, and in car parks. For example, London has several tracking systems for the Congestion Charge, the Low Emission Zone, the Dartford Crossing, as well as several other law enforcement systems for speeding and other offences [11]. In total, there are over 8500 cameras deployed in the UK which process over 25 million licence plates every day [12].

If a vehicle can be identified at several checkpoints across the road network, it is possible to build a picture of the vehicle's location over time. With more checkpoints in the road network, a more accurate tracking of the vehicle's route can be performed. Furthermore, when a vehicle is identified at one checkpoint, for example using ANPR, it is also possible to re-identify the vehicle at a later checkpoint using only it's visual characteristics [13], such as its shape and colour [14], model [15], or a combination of several features [16, 17].

Another approach that does not rely on images of vehicles is to use the patterns provided by magnetic induction loops, which differ based on the shape of a vehicle and the metals from which it is made [18]. While these systems in general are less reliable than ANPR, due to the many similarities of different vehicles, they are more robust to occlusions of certain parts of the vehicle, such as the number plate.

C. SERVICES

Attaching an external GNSS sensor requires physical access to the vehicle, but modern vehicles often disclose their location directly to LBSs, in order to provide location context to their requests. For example, the location of a vehicle can be used to improve the accuracy and speed of searches in a navigation system, or to provide information regarding local attractions. Depending on the requirements, the service might use a single location or trajectory of a single vehicle [19] or multiple vehicles. Temporal and identity information are also aspects that will need to be protected [20, 21], however, context linking attacks might be conducted to obtain a consistent identity [21].

The widespread usage of LBSs has allowed service providers to gather massive amounts of location information about where vehicles are and at what time. This information is often used to provide better services to the vehicles, such as real time traffic speeds in navigation apps such as Google Maps or Waze. However, this information can be analysed to extrapolate travel patterns and traffic analysis [2] such as an individual's driving behaviour, hobbies, home and work locations, and other personal information. The service providers are trusted to not abuse this information and to protect it from other threat actors. Further threats against historical information will be discussed in Subsection II-H.

D. VEHICLE COMMUNICATION (INSIDE VEHICLE)

Vehicles are equipped with many sensors to report on various statuses, including the wheel speeds, steering angle, and suspension movements. The majority of sensors are hardwired to an Electronic Control Unit (ECU), as this offers high reliability and fast communication. ECUs are connected via a Controller Area Network (CAN) bus (or equivalent), which can be accessed using a On-Board Diagnostic (OBD) reader on the OBD port or using vulnerabilities that enable remote access [22]. Modern vehicles typically have a GNSS sensor connected to an ECU, meaning that location is usually available via the CAN bus. Installing an OBD reader requires internal access to the vehicle, and remote access is challenging and limited, meaning it would likely be easier for a threat actor to attach their own external sensor.

Due to lower costs and practical restrictions, some sensors transmit their readings wirelessly. For example the Tyre Pressure Monitoring System (TPMS) consists of a sensor inside each tyre that transmit pressure measurements wirelessly. Messages in the TPMS contain a unique identifier that cannot be changed, and are broadcasted unencrypted [23] to a range of around 40 metres. This unencrypted broadcast enables a nearby adversary to eavesdrop the messages and identify the vehicle. Further, as the identity cannot be altered without changing the tyres, certain protection schemes (such as pseudonyms [24]) are unsuitable to protect privacy.

Another wireless vehicular communication system that uses unique identifiers, and thus are a vector for location privacy leakage is Remote Keyless Entry (RKE) [25]. When a button press is required to operate RKE a single sequence of short-range broadcasts is performed to unlock the vehicle, which is unlikely to be sufficient to track the vehicle [26]. Passive RKE (PRKE) systems, which unlock the vehicle when the key is in proximity, rely on a periodically broadcasted beacon in either the key or the vehicle. While the low power of these broadcast make them difficult to eavesdrop, this repeated communication containing the unique identifier increases the possibility of tracking and is a particular issue when the beacon is in the key, which travels with the driver even outside the vehicle.

E. VEHICLE COMMUNICATION (V2X)

While internal vehicle communications can reveal the location context of the vehicle unintentionally or through malice, some of the most likely privacy threats arise when the vehicle broadcasts its own location to cooperate with other vehicles or Intelligent Transportation System (ITS) infrastructure. The cooperative awareness message (CAM) is a European Telecommunication Standards Institute (ETSI) ITS standard that is periodically broadcasted by ITS Stations (including vehicles) [27]. CAMs are mainly used to facilitate vehicular awareness of vital traffic events by exchanging status information, where the content differs depending on the station type. For vehicles, the CAM contains the time, location, speed, heading, time, acceleration and other attributes. The information transmitted by CAMs are essential for many safety services in ITS network such as hazardous location warning, road condition warning, traffic condition awareness, and collision avoidance [28].

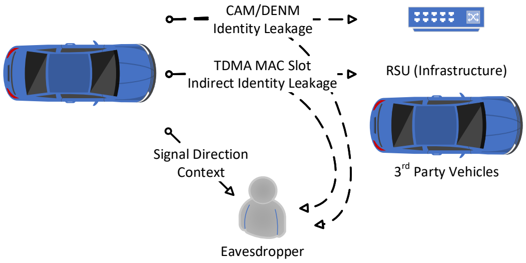

Figure 4: Vehicle Communication Threats

CAMs are sent with a digital signature that allows receivers to verify the authenticity of the message. They are not encrypted to minimise the processing time of the messages in safety critical scenarios, as the processing time is not allowed to exceed 50 milliseconds to maintain safety [27]. This combination leaks identity information (via the digital signature) and highly accurate information on where a vehicle is at a given point in time. By recording multiple CAMs a vehicle's route can be tracked. As CAMs are expected to be generated frequently (between 0.1 and 1 second [27]) this information has a very high time resolution.

In ITS networks, the applications can be classified into three groups such as traffic management, user-oriented services and safety services. Although ANPR systems are employed for traffic management, alternatives include barcodes, Radio Frequency Identification (RFID), DSRC, and Bluetooth. Barcode systems are rarely used to track moving vehicles as they are negatively affected in adverse weather conditions and, as with ANPR, require line of sight to the vehicle. Vehicles equipped with an RFID transponder can communicate with receivers on the roadside, enabling vehicle tracking and automatic toll payments [29]. In Norway, autoPASS requires vehicles to communicate with toll plazas. The unique identifier broadcasted from vehicles interacting with autoPASS can be recorded by anyone with appropriate DSRC equipment.

Safety services have mandatory requirements of bounded transmission delay and low access delay to keep the highest level of safety while user-oriented services require broad bandwidth. The Medium Access Control (MAC) layer has an important role fulfilling these needs [30]. User-oriented services are the value-added services, which can provide road information, advertisements and entertainment during the travels. One example are Time-Division Multiple Access (TDMA) based MAC protocols, that divide time into slots and allocates the slots so no more than one ITS node has access to send messages in a specific slot. The advantage of

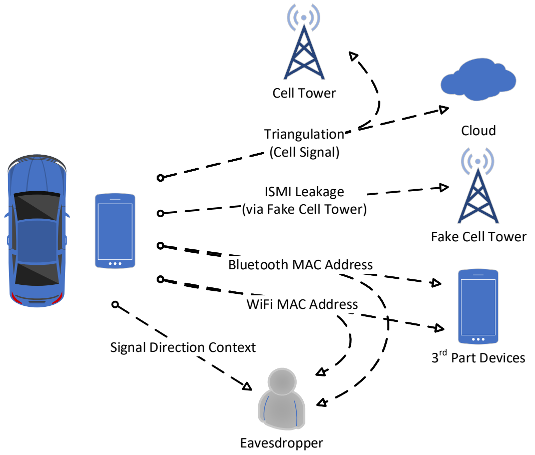

Figure 5: Non-vehicle Communication Threats

this is that wireless collisions are avoided and the timeliness of protocols can be guaranteed. However, the slot in which a vehicle broadcasts acts as an identifier. This means that a unique TDMA MAC slot will allow a semi-local threat actor to track the trajectories of vehicles by listening to the wireless communication channel. This is depicted in Figure 4.

F. NON-VEHICLE COMMUNICATION

It is not just communication from the vehicle that can leak privacy, but also communication from additional devices and peripherals within the vehicle. Some examples are shown in Figure 5, such as when a mobile phone is within range of a single cell tower, the telecommunication companies are aware that the phone is within range of that single tower. Multiple towers can be used to accurately pinpoint the location of a phone over time [31]. This information is often recorded and shared with authorities, including the police. This kind of tracking is applicable to vehicles because cellular devices are usually within the vehicle (such as mobile phone), but also because vehicles increasingly ship with cellular radios to support standards such as eSIM [32].

Many of the location privacy violations that will be presented require a unique identity to allow tracking a user over time. The first example of such an identity is the International Mobile Subscriber Identity (IMSI), which is unique across all mobile phone users worldwide. IMSI catchers are devices that can be used to obtain the IMSI of active users. The different cellular protocols require different approaches to obtain the IMSI number. Typically, a device is required to act as a fake base station that has mobile devices connect to it instead of the real base station, allowing a man-in-the-middle attack to be performed [33]. This is easy to perform in 2G/GSM as there is authentication in only one direction (the phone does not authenticate the cellular network). Man-in-the-middle attacks are possible on both 3G [34] and 4G/LTE [35]. Eavesdropping attacks against the 4G network can also allow an attacker to recover the IMSI number of targets [36]. Other techniques have also been investigated where IMSI numbers can be obtained over WiFI [37]. To avoid privacy issues with the ISMI number, Globally Unique Temporary Identifiers (GUTI) are allocated and used in most scenarios in an attempt to provide identity privacy. However, the GUTI values do not change frequently enough across a city area to obfuscate the user's identity. The work in [38, Table 1] concluded that the GUTI tended to remain the same over the 3 days a device was monitored in a city.

IMSI leakage is also likely to occur as a result of users bringing their mobile phones into the vehicle. Therefore, leaking a uniquely identifying number for users will also leak a uniquely identifying number for the vehicle the user is in. The downside is that location context is only leaked via the proxy of signal strength. An adversary would need multiple IMSI catchers, or a mobile IMSI catcher in order to track a vehicle over a long distance.

An alternative to using IMSI numbers to track users is to instead take advantage of vulnerabilities in the 4G/LTE Radio Resource Control (RRC) protocol [38]. As the user equipment (i.e., a phone) does not verify (intentionally for one case, and unintentionally — a bug — for the other) that a request for information comes from a telecommunications operator and because the request and response are unencrypted, a threat actor can trigger these messages to obtain a user's location. The responses can contain the radio tower the phone is connected or GPS coordinates if supported.

Bluetooth devices use a short range wireless link to communicate with each other. Examples of typical devices include MP3 players, wireless headphones, and mobile phones. An example of an application of mobile phones using Bluetooth is the rSAP (remote SIM access protocol), which allows a vehicle to access the SIM card of a phone to make calls. However, Bluetooth devices perform a periodic broadcast of an advertisement packet in order to inform nearby devices of their presence. Privacy is leaked by the inclusion of the device's MAC address in the advertisement packets [39]. By recording where and when Bluetooth MAC addresses have been detected, the route a device has taken can be calculated.

Cars are increasingly being equipped with IEEE 802.11 WiFi hotspots that devices within the vehicle can connect to. These hotspots are intended to offer internet connectivity via a cellular radio, or to allow devices to control certain aspects of the vehicle (such as the infotainment system). To enable connectivity WiFi, hotspots broadcast beacon frames which contain the Service Set Identifier (SSID) among other information important for devices looking to connect to the hotspot. The SSID gives the network a name and this leads to identity leakage. Similar to Bluetooth, both the hotspot and IEEE 802.11 devices will broadcast their MAC addresses [40], the channel the hotspot communicates on is another dimension that can be used to identify a target in more detail, and there are a variety of additional pieces of information that can be used to fingerprint an IEEE 802.11 device [41].

In certain cases it is not necessary for the content of the message to be leaked for an adversary to be able to trace a target. For example, in the case of Wireless Sensor Networks (WSNs) [42] the direction from which a message was received (a kind of context information) is sufficient for an attacker to trace back to a valuable asset. This direction context could be obtained using directional antennas, but it is more likely that multiple omni-directional antennas will be used instead. An attacker just receiving a CAM or DENM leaks the time and location of a vehicle. The velocity can be calculated by the difference in distance of subsequent messages, and those subsequent messages can be linked by checking that aspects of the calculated values are sensible. Examples of these checks include position change and velocity change.

G. BEHAVIOURAL DATA

Different drivers behave differently and have different styles when interacting with the controls of the vehicle [43]. Some drivers may typically brake more sharply than others at traffic lights, for example, and some drivers may maintain a consistent speed whereas others may fluctuate regularly. These differences can be used to categorise their driving style [44, 45] and to assess skill of a driver [46], but the personal driving behaviours can also be used to identify the driver behind the wheel [43, 47], or if there is a change of driver [48]. Using twelve signals from the CAN, including steering wheel angle, velocity, pedal positions, and torque, Hallac et al. [49] were able to determine the driver from data collected when a vehicle was driven around single corners.

It is possible to measure the driving behaviours visually and using RADAR, but velocity, road position, and accelerations can be observed only coarsely and intermittently. An alternative may be to use the accelerometers and other sensors in smartphones, which some apps may have permission to access. While GNSS provides the vehicle's location directly to apps, privacy conscious users may disable localisation while giving access to other sensors that do not present obvious privacy issues. For example, in [50] a magnetometer is used to detect changes in the driving angle and then map those changes onto a potential route.

H. HISTORICAL DATA

Organisations may wish to legitimately collect location information about a user after being given affirmative consent to do so. This data could be used for a wide range of purposes. For example, Google gathers the live location of users to provide a number of features, such as live traffic densities and estimated journey times, how busy a venue is, and many others. Other services such as recharging vehicles could potentially reveal privacy information due to the way the service is used over a period of time [51]. The historical data used to provide these services will need to reside in a database. The information in this database could potentially be leaked to a threat actor who was not expected to be allowed to view the database [52]. This may be through vulnerabilities, such as SQL injections, insider attacks, or other attacks.

All the live location privacy threats previously mentioned could potentially have data that leaks privacy stored in a database. This transforms the threat from gathering live information to gathering historical information. While this reduces the impact duration of the threat, it is possible to gain access to a database remotely, and the likelihood increases for threats with difficult and long setups. For example, whereas ANPR tracking requires a lengthy setup of cameras, networking, and software, accessing an ANPR database with locations can be remote and is more likely. In general, the number of vehicles impacted also increases, as a single database is likely to contain information about many vehicles.

Data summaries might be published with the intention to provide useful information but protect the privacy of specific individuals. However, it is important to ensure that privacy about a population or organisation is also not leaked. One example where this was not the case, is when the fitness tracking app Strava published heat maps of user activity and unintentionally revealed the physical layout of military bases around the world [53]. A privacy radius can be used, such that locations within a radius (typically centred on a user's home or workplace) are not disclosed. However, these are imperfect with overlapping privacy zones providing insight into their origins as well as the risk they may be part of a database leak.

If an adversary gains access to a historical database of a vehicle's location information, then it is not just past movement that is revealed but also potential future movement. There is a large body of work on predicting the location of a vehicle at a time in the future. Primarily this is for traffic flow prediction, and can be performed using Autoregressive Integrated Moving Average (ARIMA) models [54] or machine learning approaches [55]. While this may not be a direct privacy concern, it is likely the same approaches work for predicting an individuals movements. When combined with additional data, such as vehicle data [56] or geospatial information [57], location and destination prediction of individuals can be achieved with higher accuracy.

I. SUMMARY

In summary, there are many privacy threats against a vehicle, some of which are from devices within the vehicle. Table 1 presents a summary of the identified threats and includes the presence the attacker requires to take advantage of that privacy threat. This summary includes the number of vehicles impacted by the privacy threat and the attacker's presence as defined in Table 2. The attacker's presence will be elaborated on in Section III. Note that a Database Leak is shown separately as any of the previous threats could be transformed into an attack on historical data by storing it in a database.

III. THREAT ACTORS

In order to properly understand how a privacy threat will be exploited, it is necessary to understand the threat actor performing the exploitation. There exist multiple actors who wish to violate the location privacy of a vehicle. These actors

Name	Class	# Vehicles Impacted	Presence Required
Physically Attached Sensor	T_A	Single	Local
Fleet Management and Black Boxes	T_A	Single	Remote
Smartphone Sensor Data (Permission — GNSS)	T_A	Single	Remote
ANPR Tracking	T_B	Many	Semi-Local
Tracking via Visual Features	T_B	Many	Semi-Local
Location Based Services	T_C	Some	Remote
CAN Bus Access	T_D	Single	(Varies)
Vehicular Sensor Network Identifier	T_D	Single	Semi-Local
PRKE	T_D	Single	Semi-Local
Signal Direction Context	T_D / T_E / T_F	Single	Semi-Local
TDMA MAC Slots	T_E	Single	Semi-Local
CAM/DENM Identifier	T_E	Single	Semi-Local
Triangulation (e.g., via Cell Tower)	T_F	Many	Semi-Local
ISMI Catchers	T_F	Many	Semi-Local
Bluetooth Identifier	T_F	Single	Semi-Local
WiFi Identifier	T_F	Single	Semi-Local
Driving Style	T_G	Single	Semi-Local
Smartphone Sensor Data (Permissionless — Magnetometer)	T_G	Single	Remote
Database Leak	T_H	Many	Remote

Table 1: Privacy Threat Summary

Impact	Low	Medium	High
Vehicles Impacted	**Single**: A single vehicle is impacted	**Some**: A small number of vehicles are impacted	**Many**: A large number of vehicles are impacted
Threat Actor Presence	**Local**	**Semi-local**	**Remote**

Table 2: Ranking dimensions used to measure location privacy threats

each have different capabilities, resources, and expertise, which changes the ways they are able to obtain location information about vehicles. These actors also have different intents, for some threat actors the usage of this data will have a malicious purpose, others will be interested in gathering data to provide services, while others aim to benefit all road users. This section will analyse the threat actors who wish to violate location privacy and will consider the desire to protect against them.

To perform this analysis we identify four key attributes that indicate what actions threat actors can perpetrate: (i) capabilities, (ii) equipment, (iii) intent, and (iv) presence. Where capabilities indicates the knowledge, skills and experience the threat actor has, equipment specifies the resources available to the threat actor, intent is for what purpose the threat actor is violating location privacy, and presence indicates the location of the adversary.

A. THREAT ACTOR CAPABILITY

The knowledge and skills that the threat actor has will specify the threats that the threat actor can take advantage of. Typically less capable threat actors will be able to perpetrate fewer privacy violations. However, more proficient threat actors may develop highly technical privacy attacks that with the intent of providing them to less capable threat actors to deploy. The capability level will also link with the setup time before privacy can be violated, with a higher capability leading to a lower setup time.

Layman → *Proficient* → *Expert* → *Multiple Experts*

- **Layman**: Basic knowledge and low technical proficiency. Uses existing tools to exploit vulnerabilities.
- **Proficient**: Able to develop new tools to exploit vulnerabilities based on having experiences in the past.
- **Expert**: Extensive knowledge in the system domain.
- **Multiple Experts**: Multiple individuals with expert knowledge of the system. Will have insider knowledge that has not been made public.

B. THREAT ACTOR RESOURCES

The equipment that a threat actor has access to will determine which threats it is capable of taking advantage. In some of the privacy threats discussed so far, such as tracking via Bluetooth and WiFi, simple and cheap off-the-shelf equipment will be sufficient. Other threats will require standard equipment such as cameras to perform ANPR tracking. Whereas, specialised equipment would be necessary to track CAM/DENM identifiers sent over IEEE 802.11p, and bespoke equipment needed to deploy ISMI Catchers. Alternatively, it may be possible to use standard equipment such as Software Defined Radios (SDRs) instead of the specialised or bespoke equipment. For example, a threat actor could implement an IEEE 802.11p radio using an SDR rather than purchasing IEEE 802.11p equipment. The downside to this is that the threat actor would require a greater technical knowledge and the setup time would be higher.

Off-the-shelf → *Standard* → *Specialised* → *Bespoke* → *Multiple Bespoke*

- **Off-the-shelf**: Access to reasonably priced off-the-shelf equipment. This equipment will be limited in its capabilities.
- **Standard**: Access to expensive widely available off-the-shelf equipment.
- **Specialised**: Access to expensive specialised equipment.
- **Bespoke**: Able to purchase or design custom equipment, but limited to small deployments.

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Threat Actor	Motivations	Capability	Opportunity	Impact	Resources
Amateur (Cracker)	Curiosity, Self-actualisation, Passion	Layman	Open access knowledge (Low)	Unlinkable data, unidentified vehicle tracking	Low financial, Off-the-shelf equipment
Unorganised Crime (Hacktivist)	Financial gain, Vehicle theft, Passion	Proficient	Restricted knowledge (Medium)	Single identified vehicle tracking	Standard equipment
Organised Crime (Cyber Criminal)	Financial Gain, Ideology	Expert	Sensitive knowledge (Medium or High)	Single or multiple identified vehicle tracking	Specialised Equipment
Organised Corporation	Financial Gain, build services based off data, Ideology	Multiple Experts	Sensitive knowledge (High)	Multiple identified vehicles tracking	High financial, large bespoke deployments
Government	Improve infrastructure, track criminals, Political	Multiple Experts	Critical knowledge (Critical)	Single-multiple identified vehicles and traffic tracking	Nationwide bespoke deployments

Table 3: Example Threat Actors

- **Multiple Bespoke**: Able to purchase or design multiple pieces of custom equipment and deploy in bulk.

C. THREAT ACTOR INTENT

It is important to understand the intent of a threat actor. Different threat actors intend to collect data that violates the privacy of a vehicle for different reasons. The typical intent that is protected against is malicious, where the threat actor intends to violate privacy in order to cause harm to the vehicle or person privacy is violated against. However, in other cases the threat actor may not intend to violate privacy of users, but may unintentionally reveal it to many people. Common examples include government officials leaving unencrypted disks on public transport. It may also be the case that privacy violating information is collected to improve the lives of people the data is gathered about. Privacy preserving techniques will be different when considering different intends of the threat actor. Additional techniques will also be available to benign and unintentional threat actors to protect privacy.

$$\textit{Benign} \rightarrow \textit{Unintentional} \rightarrow \textit{Malicious}$$

- **Benign**: A threat actor that collects information that is kept secure and private. The information is used for *good* purposes, such as providing a service, or improving the transportation network.
- **Unintentional**: A threat actor that collects information and intends to keep it secure and private, but fails to do so. This may be due to poor security leading to data breaches, or released datasets not being properly anonymised.
- **Malicious**: A threat actor that intentionally obtains information that aims to use it for *nefarious* purposes. This may involve releasing or selling unanonymised data.

D. THREAT ACTOR PRESENCE

The presence of the threat actor is important in understanding the threats it can perpetrate. A local threat actor will be capable of perpetrating more privacy violations, but this comes at an increased difficulty and risk for the threat actor (such as capture by authorities). Whereas remotely violating privacy is limited in the privacy violations that can be performed, but comes with a lower risk to the threat actor. There is also an impact regrading the quantity of vehicles that a threat actor can violate privacy, as semi-local and remote threat actors will likely be able to impact more vehicles' privacy.

$$\textit{Internal} \rightarrow \textit{Local} \rightarrow \textit{Semi-Local} \rightarrow \textit{Remote}$$

- **Internal** presence is when the threat actor is able to access the inside of the vehicle. This includes physical access to components within the vehicle's body, but also if malware is deployed to internal components remotely.
- **Local** presence is when the threat actor is physically located outside of the vehicle (typically within several meters of the vehicle). This threat actor is able to attach devices to the outside of the vehicle.
- **Semi-Local** presence is when the threat actor is physically nearby the vehicle. They may be out of sight of the vehicle, but still in wireless range. This threat actor may be capable of eavesdropping or visually observing vehicles.
- **Remote** presence is when a threat actor only has access to vehicle information via the internet. This threat actor is incapable of observing the vehicle locally, but may gain control of devices within the vehicle in order to obtain **Internal** presence to observe events.

E. EXAMPLE THREAT ACTORS

A table of example threat actors is shown in Table 3 which is created based on the works in [58, 59, 60]. These threat actors are specific examples of different combinations of intent, capabilities, and resources, but also includes details specifying the threat actor's: *motivations* (why does it want to violate location privacy), *opportunity* (how aware of situations in which privacy can be violated), and the *impact* it can have on location privacy. It is important to consider who is violating privacy, because there will be limitations to the privacy a technique can achieve based on the type of threat actor that is violating privacy.

IV. PRIVACY PRESERVING TECHNIQUES

With an understanding of the threats to vehicular location privacy and the threat actors that perpetrate the threats, the techniques used to provide privacy can be examined. There has been much work performed in developing techniques to protect location privacy. This section will examine privacy protection techniques and classify them into five categories: (A) Signal Jamming, (B) Perturbing Identity, (C) Perturbing Data, (D) Changing Communication Patterns, and (E) Changing Behaviour. These categories are intentionally broad due to the wide range of privacy threats being considered. More specific categorisations have been considered in other work that focuses on specific location privacy threats (such as in [1]), but are not suitable for the broad range of threats being considered in this work.

A. JAM SIGNAL

To protect against certain types of threat a vehicle may seek to jam signals being broadcasted. For example, if a threat actor has attached a GNSS sensor to the vehicle, then jamming the GNSS signal would prevent location logging. The downsides are that (i) the vehicle would also not be aware of its location via GNSS, (ii) an additional signal is present that a threat actor could possibly track, and (iii) GNSS jamming is illegal in many parts of the world (e.g., Title 47 U.S.C §§ 301, 302(b) and 333 for the USA and Section 68 of the Wireless Telegraphy Act 2006 for the UK). For many threats, jamming signals would be unsuitable to provide location privacy because it denies availability.

B. PERTURBING IDENTITY

To protect the identity, one option is to encrypt the uniquely identifying number broadcasted in messages. For example, in a TPMS encrypting the per sensor identifier while leaving the rest of the message unencrypted protects the identity and facilitates issue diagnosis by humans due to the unencrypted contents [61]. Each time a message is broadcast a different encrypted value would be sent, essentially making it appear as if a random identifier was being used. This means that the message contents can still be used by existing tools, meaning both backwards compatibility and privacy are provided. To obtain a stronger encryption the authors of [61] propose the encrypted identifier be lengthened from 32 bit to 64 bit, but this would break backwards compatibility.

This technique works for TPMS because the sender and receiver are only a single communication hop away from each other, and hardware deployers can ensure the vehicle is aware of what TPMS identifiers to expect and how they will be encrypted. For other systems that do not have such a tight integration, this approach of encrypting the identifying information such that it is different with each broadcast may not be feasible.

To enable vehicle tracking, having a consistent identity that can be observed at different locations and times allows a threat actor to link individual observations into a more comprehensive dataset of the route taken. One of the key techniques to protect location privacy of vehicles is the use of temporary pseudonyms that change frequently. By changing pseudonyms the threat actor is less able to link between individual observations [62]. Such a technique is useful for a variety of communication protocols, such as V2X, WiFi, Bluetooth and others. How the pseudonym change is managed is important, as other vehicles need to be quickly updated when identities are revoked [63] while minimising the likelihood of an adversary being able to link pseudonyms [64].

Pseudonyms can be used in different circumstances. For example, a benign threat actor may be gathering data (which they have been given permission to do so) and anonymising the data by generating pseudonyms for users themselves. Alternatively, the vehicles themselves may be periodically changing the pseudonyms they broadcast to other vehicles and road-side infrastructure to protect against data gathering by malicious threat actors.

A recent innovation that is currently being experimented with are digital number plates [65]. They use an e-ink display to show the vehicle's registration number and open the possibility to show alerts that change along with other messages. Because the number plate displayed is customisable, the registration number could be a pseudonym that is periodically changed. As this technique would then be similar to pseudonyms used in wireless broadcast techniques, unlinking strategies would be needed to ensure the old pseudonym could not be linked to the new pseudonym. An alternate approach could be to use adversarial machine learning. As the display on the number plate is customisable, it may be possible to display a pattern that prevents the optical character recognition component of ANPR from being able to discern the characters in the number plate [66].

Identity anonymity-based approaches are also used to preserve the location privacy of LBS users. This is necessary because LBS providers are assumed to correctly process and respond to requests, but they may attempt to disclose identity of a user [67]. k-anonymity [68] is one of the most popular anonymity-based approaches, where it focuses on controlling the release of *quasi-identifiers* of users in a dataset, where quasi-identifiers are a combination of characteristics that enable linking to a user. The technique requires that the each quasi-identifier of an individual must be indistinguishable from $k-1$ other individuals, where $k>1$.

In the context of protecting vehicular location privacy within LBSs, a linking attack is successful if the user's location is revealed by the queries sent to a LBS. Anonymity can be achieved by cloaking a location area, such as by New Casper [69], Prive [70], and PrivacyGrid [71] which provide k-anonymity by cloaking an area that contains at least k users at the time of a query submission. Other approaches involve using *dummy* locations to mask a user's real location [72], or allows user to set a minimum level of anonymity desired and the maximum temporal/spatial tolerance that they are willing to accept [67].

However, it can be difficult to achieve k-anonymity for LBS users in practice. The number of k-vehicles may be smaller in sparse traffic and a large cloaked location area may be impractical for many LBSs. Furthermore, a shortcoming of k-anonymity is that if an adversary has sufficient background information it may be capable of distinguishing an individual from the k others [73].

There are limitations to perturbing identity because certain aspects of the vehicle are immutable (or sufficiently difficult to change). For example, the colour and shape of a vehicle can contribute to uniquely identifying it and both would be difficult to change. Also as digital licence plates are in their infancy, nearly all vehicles will be fitted with standard number plates which require time and effort to change. The frequency that these kinds of identity can be changed is lower than other aspects of identity (such as wirelessly broadcast pseudonyms), which means they can be used to link higher rate identity change techniques.

There can also be limitation against specific privacy threats. For example, using temporary pseudonyms to prevent tracking of WiFi devices is insufficient as there are a number of implicit characteristics of using WiFi devices (network destinations, advertised SSIDs, IEEE 802.11 options, and sizes of broadcast packets) that allows a threat actor to be able to potentially identify a device [41]. This means that multiple privacy preserving techniques will need to be used for a subset of privacy threats.

C. PERTURBING DATA

Privacy of individuals can be also protected by perturbing the records in a database. The existing data perturbation techniques include additive noise, aggregation, swapping records, or generating synthetic data based on statistics of the original data [74]. Data perturbation techniques can be simple and cost-efficient compared to other Privacy Preserving Data Mining techniques [75]. A common classification of data perturbation techniques are input and output perturbation. Input perturbation techniques adjust the data provided to a service or function; and output perturbation performs the computation on the original data, but the result is provided with added noise [76, 77].

Among these techniques, Differential Privacy (DP) is useful due to the formal quantification of the provided privacy. Centralised Differential Privacy (CDP) and Local Differential Privacy (LDP) are the two main models used to achieve DP, however, there are emerging studies on hybrid DP models [78]. CDP performs output perturbation where the original data is aggregated in a trusted curator and the amount of perturbation is calibrated according to the query outputs. The aim of CDP is to ensure query outputs are nearly identical with addition or removal of a single record in a database. Input perturbation techniques such as Randomised Response [79] can be used in LDP. In LDP, data owners perturb their data before transmitting it to other parties. Computation and analysis is then run on the perturbed data which mean there is no need for a trusted curator when applying LDP. Therefore, LDP provides stronger privacy guarantee than CDP but results in greater noise [80].

The notion of geo-indistinguishability [81] is proposed to preserve the exact locations of individuals in a radius r with the level of privacy preserving depending on r and a distance-based probabilistic noise is introduced to the location data. However, due to the distance based sensitivity measurement and sparsity of location dataset, it might be needed to add a large amount of noise to ensure DP. Cormode et al. [82] applied a hierarchical tree structure to decompose geometric areas into smaller areas. Herewith, they could reduce the amount of needed noise. Ou et al. [83] claimed the privacy model should not only consider the privacy of a single user of a LBS, but should also consider location correlation among multiple users. The authors proposed a model to quantify location correlation of two users using a hidden Markov model and protect the multi-user location correlation via a differentially private trajectory release mechanism. DP techniques promise a rigorous level of privacy, however, there are limited applications that have adopted DP in practise. Some examples where DP has been proposed to be used include: scheduling the recharging of electronic vehicles [84] where the location of the vehicles are perturbed, vehicle platooning [85], and streaming data of multiple vehicles to Edge services [86].

D. CHANGING COMMUNICATION PATTERNS

As the MAC time slot assignment can be linked to the identity of a vehicle, if a vehicle changes its pseudonym then the MAC time slot remaining the same would allow a threat actor to link the old and new pseudonym. The work in [87] synchronises the change in MAC time slot and pseudonym to prevent the attacker from performing this linking.

To prevent a threat actor from gaining information, one option is for the vehicle and the devices to cease broadcasting for sufficient time to reduce the linkability of its location before it stopped broadcasting and the location after it starts broadcasting again. In most situations this is undesirable as it limits the availability of the services being provided, which could potentially lead to safety issues. It would also be unacceptable to users to cut off certain services whilst they are in use (e.g., during a call). However, there are some situations where staying silent does not lead to a significant safety decrease. For example, CAM pseudonym schemes rely on a silent period after changing pseudonyms in a large group to prevent linkability between the old and new pseudonyms [62]. Without the silent period a threat actor

Class	Name	Privacy Protection	Feasibility	Cost
P_A	Jam Signal	Denies access to GNSS sensor, or a communication link.	Low feasibility. Jamming is illegal in many places. Users will still want services.	Denies availability to services that are jammed.
P_B	Encrypt Unique Identifier	Prevent identity leakage.	Useful in specific circumstances, but infeasible in general.	Computational and communication overhead.
	Temporary Pseudonyms	Decorrelates identity of vehicle at specific time and location	High. Useful to many different privacy threats.	Computation and communication in obtaining pseudonyms and handling identity change. Safety costs in some applications (due to required silent period).
	k-anonymity	Group k data of individuals into a range to make each individual indistinguishable from $k-1$ others.	High. Can be used to group LBS users	Challenges when data has high-dimensionality, plus vulnerabilities to composition and background knowledge attacks.
P_C	Differential Privacy	Ensures the outcome of any analysis is not significantly affected by the removal or addition of a single record by perturbing data in a controlled manner.	Useful for providing a strong privacy guarantee but can be difficult to apply to real-life applications.	Introduces a trade off between privacy and efficacy (e.g. Privacy and Safety, Privacy and Efficiency).
	Generative Adversarial Networks	Generates new datasets with similar patterns based on large anonymised datasets.	High in general. Computationally expensive and still relies on a large quantity of real-world data.	Generated data is not real-world data and may not share all its detail and properties, meaning applications or models using it may be less successful. Privacy is not guaranteed and synthetic data may disclose information about participants in the training set.
P_D	Vary Transmit Time	Decorrelate the time at which a message was sent.	High in general. Low for applications where low latency is important.	Increase in delivery latency.
	Vary Transmit Power	Decorrelate the location and direction from which a message is sent.	High.	Decreased range in which other vehicles can receive messages.
	Cease Broadcasting	By not broadcasting a signal is not available for a threat actor to track.	Low in general, as this denies availability to the services provided. In specific use cases this may applicable.	Denies service availability.
P_E	Change route taken	Instantaneous position leaked, obfuscation over long-term history.	Limited by opportunities to drive in different ways (e.g., by road network layout and network degree).	Increased cost to driver (fuel, mental effort - thinking of new routes).

Table 4: Privacy Provision Techniques Summary

would be able to link the CAM pseudonyms.

Another approach to providing privacy in vehicular ad-hoc networks (VANETs) is to perturb packet routing. To protected the location privacy of a receiver, in [88] a packet is sent to a social spot which vehicles frequently visit instead of being forwarded directly to the target. When the target arrives at the social spot they are then able to collect the message without the sender knowing where the target was.

The Received Signal Strength Indicator (RSSI) indicates how strong a wireless signal is while a message is being received. Based on this value the distance of the vehicle can be estimated [89]. By varying the transmit power of DSRC the accuracy of the localisation of the vehicle can be reduced.

To resolve the issues with the way Bluetooth devices leak identity information that facilitate tracking, in the Bluetooth 4.2 standard a new feature called Bluetooth LE Privacy was introduced. The aim of this technology is to randomise the MAC address used to advertise the device [90, 91]. Once devices are paired they will both possess an Identity Resolution Key (IRK) which allows translation of the randomised MAC address into the real MAC address. This way devices can connect to each other and know if identity of the connected device, but observers see MAC addresses that appear to randomly change at a rate set by the manufacturers.

It is important that manufacturers provide a way to disable backwards compatibility with the old advertising technique, because if it and Bluetooth LE Privacy are both enabled then no privacy is provided. For example, in 2016 a report into fitness tracker privacy found that all devices except one of those investigated leaked persistent MAC addresses by not using Bluetooth LE Privacy [92].

For WiFi additional perturbations need to be made as it can be insufficient to just change pseudonyms [41]. Additional aspects of using WiFi also need to be varied, including:

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network destinations, SSID probes, broadcast packet sizes and MAC protocol fields.

In order to track vehicles a correlation often needs to be made between where and when the vehicle was detected. In order to prevent correlation, messages can be delayed and reordered [93]. However, this has limited uses in a vehicular context, as many message will be safety critical and therefore need to have minimal delay.

Rather than delaying and reordering messages, if possible the messages could cease broadcasting. This technique would only be feasible to be used to protect certain types of privacy threats. For example, in PRKE systems, the key does not need to inform the car to unlock the doors when the driver is still in the car or while the car is moving. The key could detect these and similar scenarios and cease broadcasting the beacon [94] to provide privacy.

E. BEHAVIOUR CHANGE

A vehicle can be tracked more easily if it takes the same route each day, compared to when its route varies. In particular, it is possible to use the same static sensors and cameras to track the vehicle when the same route is taken. One way to increase privacy, therefore, is to vary the route taken by a vehicle each day. Ideally, this would mean changing the end destination and the roads taken to get there. However, commuters typically travel to a single destination, meaning the vehicle is only able to vary the route taken. In this way, the vehicle is seen by different trackers and some uncertainty is introduced to its whereabouts and/or destination. However, with networked or centralised identification and tracking over a sufficiently large area, altering routes taken each day will likely be ineffective in providing privacy.

F. OPTIONS AVAILABLE TO A BENIGN THREAT ACTOR

To a threat actor that has gathered location information data for a non-malicious purpose there are additional techniques to protect privacy that those organisations can take. It may be important for them to provide this protection as there may be financial (e.g., fines) or reputation repercussions that the organisation wishes to avoid.

One of the simplest techniques to protect privacy is to delete the gathered information. For example, Transport for London is only authorised to keep ANPR tracking data for up to 28 days and the London Police are allowed to keep it for a maximum of 2 years [11]. By deleting the data it will not be a resource that another threat actor could attempt to obtain.

An alternate to differential privacy may be to use Generative Adversarial Networks (GANs) [95]. GANs can be trained on the anonymised location traces stored in a database, and then be used to generate a new dataset with similar patterns to the datasets it was trained on. This could potentially allow a dataset to be released to the public (or sold to another entity) whilst protecting the privacy of the users whose location data was used to generate the new dataset. This technique would only be applicable to benign threat actors.

G. SUMMARY

There are many options to protect location privacy threats which are summarised in Table 4. However, to protect location privacy a trade-off often needs to be made. For example, when changing pseudonyms used in CAM a silent period is needed to decorrelate the previous identity of a vehicle from the subsequent identity. This silent period means that some safety is traded for the proper functioning of the privacy preserving technique. It is important to understand what users are giving up in order for privacy to be provided. In some cases the cost may be too high compared to the privacy gained.

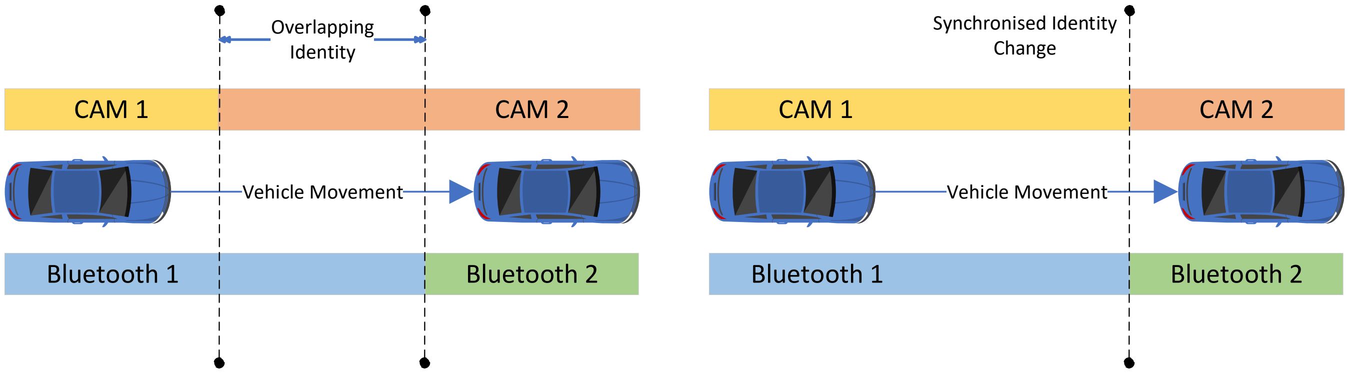
V. ANALYSIS

The techniques presented in Section IV mostly focus on individual issues, with the exception being MAC slots and pseudonyms in [87]. Therefore, in the next section we analyse the interactions between privacy preserving techniques. The focus of this analysis is on the impact of applying a new privacy preserving technique while another technique is already being used to protect against a different privacy threat. Furthermore, when determining how to preserve privacy it is useful to understand how difficult it is for a threat actor to exploit a privacy threat. So, in Subsection V-B we classify the threats in two dimensions, namely directness and timeliness. This classification is used to understand what kinds of threats will be carried out by different threat actors and the feasibility of them exploiting these privacy threats due to their resources and capabilities.

A. IMPACT OF TECHNIQUE INTERACTION

Considering privacy preserving solutions independently without considering their interactions leads to ways in which live location privacy is not protected. For example, when a vehicle changes its pseudonym in broadcasted CAMs, unless all the other techniques that also include a broadcasted identity change that identity simultaneously no privacy will be provided. This is because an adversary will be capable of linking the old CAM identity to the new CAM identity via the other sources of identity within the vehicle. An example of this is shown in Figure 6 with a time period in the centre where an attacker can link pseudonyms. This is problematic for vehicles because there are many devices present in the vehicle that it may not have authority over to manage which pseudonyms are used to certain points, or how other privacy preservation techniques work. For example, techniques such as [96] which provides location privacy in cellular networks using pseudonyms would need to collaborate with a vehicle to schedule pseudonym changes. Such scheduling may be impossible, as [96] requires a cell phone be in the process of switching towers, which may not occur when a vehicle intends to change pseudonym (such as at an intersection [24]).

To understand how threats and techniques relate, Figure 7 shows a mapping between the class of threats and class of solutions that can be used to provide location privacy for that threat. This mapping has been created by first classifying



(a) Overlapping Identity Change

(b) Synchronised Identity Change

Figure 6: Identity Change Interactions

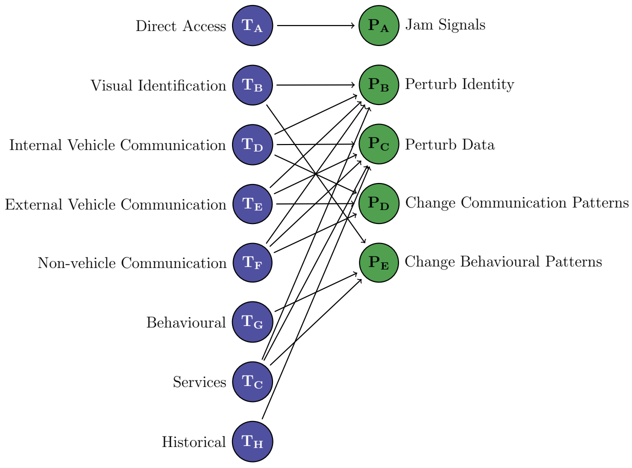

Direct Access
Visual Identification
Internal Vehicle Communication
External Vehicle Communication
Non-vehicle Communication
Behavioural
Services
Historical
T_A
T_B
T_D
T_E
T_F
T_G
T_C
T_H
P_A
P_B
P_C
P_D
P_E
Jam Signals
Perturb Identity
Perturb Data
Change Communication Patterns
Change Behavioural Patterns

Figure 7: Mapping of Location Privacy Threat Classes to Privacy Preserving Technique Classes

privacy threats in Section II, classifying privacy techniques in Section IV, and then observing the class of techniques that can be used to protect against threats in a specific class.

Using this mapping between threats and techniques, a matrix of privacy threat interactions is presented in Figure 8 which is generated from Methodology 1[1]. It shows how the privacy preserving technique for the threat on the left may need to be changed when the privacy threat on the top is being considered. For some threats multiple aspects of the privacy techniques need to be considered (two triangles of different colours), but for others the entry is empty because the solution interaction either does not interact or there are no overlapping ways to protect privacy, and therefore changes do not need to be made to the privacy preserving technique. This interaction matrix is intended to be updated as new techniques are developed, or new privacy threats are identified.

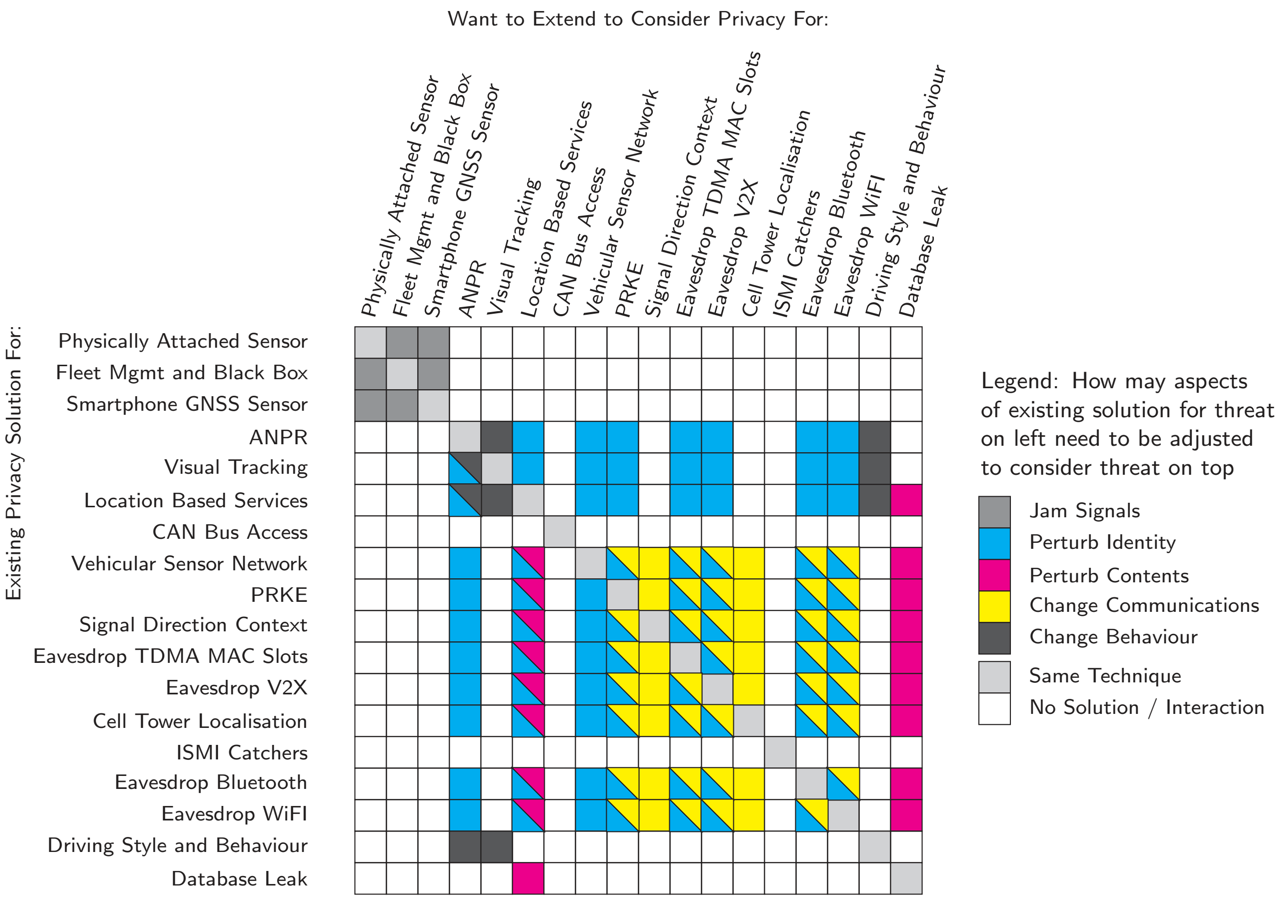
The interaction matrix in Figure 8 highlights that privacy preserving techniques that previously used only one kind of protection may need to use new kinds of techniques when considering new threat combinations. For example, when broadcasting over WiFi, Bluetooth or DSRC (e.g., IEEE 802.11p) the device's identity needs to periodically be changed. But when considering threat actors who are analysing the directional context of signals, the transmit power or transmit time needs to also be varied to protect location privacy.

Similar considerations are need when privacy preserving techniques of different kinds of threats interact. For example in LBSs when moving from one area to another the vehicle's LBS queries will be mixed with a different set of vehicles,

Methodology 1 Technique Interaction

```
▷ What changes in the provision of privacy against $\text{threat}_1$ might need to be made when also protecting against $\text{threat}_2$?
function COMBINE($\text{threat}_1, \text{threat}_2$)
▷ Get the set of techniques used to protect against these two specific threats
    $\text{technique}_1 \leftarrow \textsc{Technique}(\text{threat}_1)$
    $\text{technique}_2 \leftarrow \textsc{Technique}(\text{threat}_2)$
    if $\text{threat}_1 = \text{threat}_2$ then
        return $\text{technique}_1$
    ▷ Which techniques are used by both threats?
    $\text{comb} \leftarrow \text{technique}_1 \cup \text{technique}_2$
    ▷ The threat class the specific threats are in
    $\text{threatcls}_1 \leftarrow \textsc{ThreatClass}(\text{threat}_1)$
    $\text{threatcls}_2 \leftarrow \textsc{ThreatClass}(\text{threat}_2)$
    ▷ The techniques used to protect a threat class
    $\text{threattech}_1 \leftarrow \textsc{ThreatTechniques}(\text{threatcls}_1)$
    $\text{threattech}_2 \leftarrow \textsc{ThreatTechniques}(\text{threatcls}_2)$
    ▷ Which techniques are used by $\text{threattech}_2$?
    $\text{comb} \leftarrow \text{comb} \cup \text{threattech}_2$
    ▷ Only consider techniques able to protect against $\text{threat}_1$
    $\text{comb} \leftarrow \text{comb} \cap \text{threattech}_1$
    return comb
```

[1] Figure 8 generation code available at: https://github.com/MBradbury/vehicle-privacy-analysis



Want to Extend to Consider Privacy For:

Existing Privacy Solution For:

	Physically Attached Sensor	Fleet Mgmt and Black Box	Smartphone GNSS Sensor	ANPR	Visual Tracking	Location Based Services	CAN Bus Access	Vehicular Sensor Network	PRKE	Signal Direction Context	Eavesdrop TDMA MAC Slots	Eavesdrop V2X	Cell Tower Localisation	ISMI Catchers	Eavesdrop Bluetooth	Eavesdrop WiFI	Driving Style and Behaviour	Database Leak
Physically Attached Sensor	░	▦	▦	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜
Fleet Mgmt and Black Box	▦	░	▦	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜
Smartphone GNSS Sensor	▦	▦	░	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜
ANPR	⬜	⬜	⬜	░	⬛	🟦	⬜	🟦	🟦	⬜	🟦	🟦	⬜	⬜	🟦	🟦	⬛	⬜
Visual Tracking	⬜	⬜	⬜	🟦/⬛	░	🟦	⬜	🟦	🟦	⬜	🟦	🟦	⬜	⬜	🟦	🟦	⬛	⬜
Location Based Services	⬜	⬜	⬜	🟦/⬛	⬛	░	⬜	🟦	🟦	⬜	🟦	🟦	⬜	⬜	🟦	🟦	⬛	🟪
CAN Bus Access	⬜	⬜	⬜	⬜	⬜	⬜	░	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜
Vehicular Sensor Network	⬜	⬜	⬜	🟦	⬜	🟦/🟪	⬜	░	🟦/🟨	🟨	🟦/🟨	🟦/🟨	🟨	⬜	🟦/🟨	🟦/🟨	⬜	🟪
PRKE	⬜	⬜	⬜	🟦	⬜	🟦/🟪	⬜	🟦	░	🟨	🟦/🟨	🟦/🟨	🟨	⬜	🟦/🟨	🟦/🟨	⬜	🟪
Signal Direction Context	⬜	⬜	⬜	🟦	⬜	🟦/🟪	⬜	🟦	🟦/🟨	░	🟦/🟨	🟦/🟨	🟨	⬜	🟦/🟨	🟦/🟨	⬜	🟪
Eavesdrop TDMA MAC Slots	⬜	⬜	⬜	🟦	⬜	🟦/🟪	⬜	🟦	🟦/🟨	🟨	░	🟦/🟨	🟨	⬜	🟦/🟨	🟦/🟨	⬜	🟪
Eavesdrop V2X	⬜	⬜	⬜	🟦	⬜	🟦/🟪	⬜	🟦	🟦/🟨	🟨	🟦/🟨	░	🟨	⬜	🟦/🟨	🟦/🟨	⬜	🟪
Cell Tower Localisation	⬜	⬜	⬜	🟦	⬜	🟦/🟪	⬜	🟦	🟦/🟨	🟨	🟦/🟨	🟦/🟨	░	⬜	🟦/🟨	🟦/🟨	⬜	🟪
ISMI Catchers	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	░	⬜	⬜	⬜	⬜
Eavesdrop Bluetooth	⬜	⬜	⬜	🟦	⬜	🟦/🟪	⬜	🟦	🟦/🟨	🟨	🟦/🟨	🟦/🟨	🟨	⬜	░	🟦/🟨	⬜	🟪
Eavesdrop WiFI	⬜	⬜	⬜	🟦	⬜	🟦/🟪	⬜	🟦	🟦/🟨	🟨	🟦/🟨	🟦/🟨	🟨	⬜	🟦/🟨	░	⬜	🟪
Driving Style and Behaviour	⬜	⬜	⬜	⬛	⬛	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	░	⬜
Database Leak	⬜	⬜	⬜	⬜	⬜	🟪	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	⬜	░

Legend: How may aspects of existing solution for threat on left need to be adjusted to consider threat on top

- ▦ Jam Signals
- 🟦 Perturb Identity
- 🟪 Perturb Contents
- 🟨 Change Communications
- ⬛ Change Behaviour
- ░ Same Technique
- ⬜ No Solution / Interaction

Figure 8: Threat interaction matrix showing possible ways in which privacy preserving techniques for privacy threats on the left may need to be adjusted to consider privacy threats on top.

because of this the vehicle should change its identity (which should lead to other devices in the vehicle changing their identities) to prevent linking between the two different areas. Alternatively as indicated by Figure 8 the contents of V2X messages may need to change to protect privacy (such as the included location). However, due to the functional constraints on the accuracy of these messages (i.e., to ensure safety), protecting privacy in this manner may be infeasible. This is because the broadcasted location needs to be highly accurate in order for other vehicles to make reliable decisions about actions to maintain safety.

Therefore, there is a need to understand how multiple privacy threats and the techniques to protect against those threats will interact in order to design privacy preserving techniques which continue to provide privacy under this interaction. It is also necessary to understand the impact of functional requirements and how there may be a trade-off between these requirements and the level of privacy that can be provided.

B. THREATS CLASSIFICATION

Thus far threats have been allocated to classes based on how identifying information is revealed to an adversary. However, we can classify these threats differently based on the *directness* of how this information is revealed and the *timeliness* which represents the age of the information.

Direct access to the location means that a threat actor can see where the vehicle currently is over time, without any further processing. For example, coordinates from a GNSS sensor provides the location over time with high fidelity and can be immediately viewed on a map. Indirect access requires some processing in order to extract or interpolate detailed trajectories. ANPR systems are able to view a vehicle driving through a road network, but the data is sparse and must be interpolated estimate where the vehicle is over time.

- *Directness*: What data does the threat actor obtain and how does it reveal the location of the vehicle?
  - **Direct**: The data specifies the location of vehicle.
  - **Indirect**: The data needs to be analysed to obtain the location of the vehicle.
- *Timeliness*: When is the data from?

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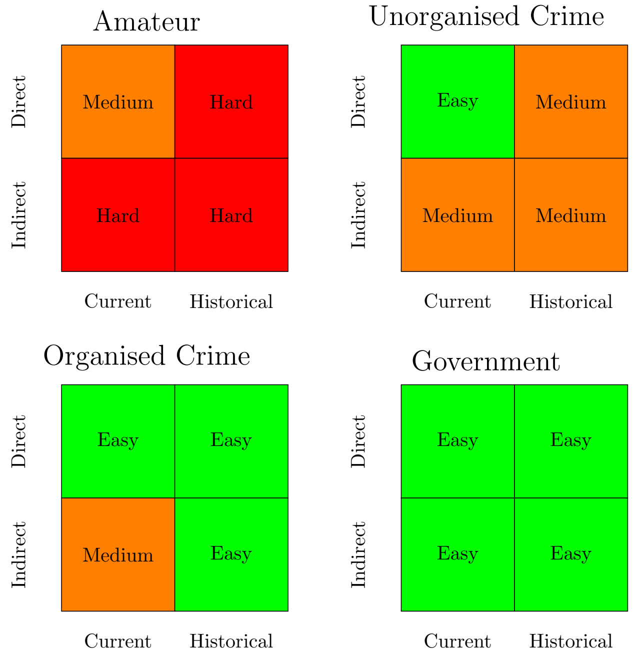

Amateur

	Current	Historical
Direct	Medium	Hard
Indirect	Hard	Hard

Unorganised Crime

	Current	Historical
Direct	Easy	Medium
Indirect	Medium	Medium

Organised Crime

	Current	Historical
Direct	Easy	Easy
Indirect	Medium	Easy

Government

	Current	Historical
Direct	Easy	Easy
Indirect	Easy	Easy

Figure 9: Difficulty Table

- **Current**: The threat actor has access to the live stream of data.
- **Historical**: The threat actor has access to old data.

In Figure 9 the difficulty of different classes of threat actors violating different classes of privacy threats is shown. Note that violating real-time privacy is typically harder than violating historical location privacy [21]. A real-time violation requires an attacker to either set up their own network of sensors, or gain access to an existing system. In either case, they must have the capabilities to process the data in real-time, and they may be thrown off a breached system at any time. A historical violation requires only access to a database, or database leak. This allows the attacker to proceed in their own time, and reduces the computational requirements.

The impact of violating different classes of privacy can be different based on the historical data present. A real-time attack allows the vehicle's current location to be revealed and significant information may be inferred from historical data depending on its age and time period. For example, if a historical violation grants access to old and out of date information, it may be less relevant to the vehicle and its user. However, historical data from a recent time period, or over a long duration can have a greater impact because it can be used to infer additional information about the vehicle's user. For example, by pattern of life analysis an adversary could predict where the vehicle will be in the future. This means both historical and real-time privacy threats can have high impact.

VI. DISCUSSION

This paper has examined many privacy threats, threat actors interested in violating privacy, and privacy preserving techniques. However, there are many additional considerations when considering vehicular location privacy, especially as there are instances where tracking of vehicles is necessary, and other cases where violating privacy leads to a greater utility than protecting privacy. This section will discuss some of these additional issues around vehicular location privacy.

A. WHO SHOULD WE EXPECT TO BE ABLE TO TRACK VEHICLES?

This work has focused on the protection of vehicular location privacy, but there are many examples where users gain utility from revealing their location. Users will want to provide locations to LBS in order to get recommendations that are targeted to their journey. Autonomous vehicles will want to inform nearby vehicles of their location, velocity, identity and the time at which this data was recorded to ensure that other vehicles collaborate to ensure that no safety properties are violated. Toll Roads and Car Parks will track vehicles to ensure the owners are correctly billed for using those services. It is also the case that Governments will want to understand the behaviour of their citizens to better design services in a cost effective manner based on where demand is. The police force of a country will need to be able to track vehicles to ensure that criminals can be apprehended. For example, the EU Cross-Border Enforcement Directive [97] aims to track users who commit traffic offences in an EU member state different to the one the vehicle is registered in. Part of this directive involved sharing databases on drivers, which may contain sensitive location information.

These are just a subset of examples where vehicle tracking is required. There are many use cases where a user desires location information to be shared, where there is a contractual requirement to share location information, and where there is a legal requirement to share location information. It is important to consider these cases and their interactions with location privacy threats and techniques, as they add additional considerations when location privacy needs to be provided. However, they potentially allow privacy provision to be ignored and the cost of providing privacy protection to be avoided under certain use cases.

B. ACCEPTABLE PRIVACY VIOLATIONS

In certain cases the desire to remain private may be exceeded by the utility gained by a user revealing their location. One example of this is the eCall system, where upon a serious collision authorities will be automatically notified. The data sent to them may include "the triggering mode (automatic or manual), the vehicle identification number, vehicle type and propulsion, timestamp, vehicle direction, current and previous positions, and number of passengers" [98]. The key aspect of eCall is that it does not broadcast continuously, but only in case of an emergency. This means that no privacy is leaked during the normal use of the vehicle. However, in rare circumstances where lives are at risk the vehicle will intentionally leak privacy with the intent to speed up life saving responses. It is likely most users would be willing to give up privacy in these scenarios in order to obtain a higher chance of survival.

C. LIMITATIONS

Many social media sites and messaging apps allow a user to provide their location to the LBS which is then shared with other users of the service. In some cases the user will share with a select few people, but in other cases the user may not have set up their privacy settings and will broadcast their location publicly on the internet. In this scenario, the user has wilfully chosen to opt-out of location privacy and therefore it is unnecessary to attempt to consider the privacy protection interactions from other privacy threats.

For some scenarios it may be desirable to provide short-term linkability, but long-term unlinkability. This means that in one event each vehicle should be aware of who is present, but in subsequent events it should not be possible to link vehicles between participating in these events. This long-term unlinkability will only be protected again certain threat agents, such as other vehicles on the road or malicious eavesdroppers. There may be the need to unpack the long-term unlinkability of a vehicle by a trusted authority. For example, in the case of a car crash the investigators and insurance companies may need to violate privacy in order to determine the events that occurred. Such a scheme could be provided by group signatures in [99]. An issue with this approach is that the trusted authority who issues the group signing keys and maintains a database of how to reveal the identities becomes a new privacy threat.

D. EFFECT OF AUTONOMY

As autonomous vehicles are going to become increasingly common on roads, they will lead to new privacy threats, but will also reduce the risk of existing privacy threats. For example, currently it is possible to use vehicle sensor data to identify different driving styles and drivers from their driving signatures [100, 101]. Once a driver's identity is disclosed, it allows linking other trajectories to that driver. However, the driving signatures will become less useful with fully autonomous vehicles because a human driver will not be in control of the vehicle. Any analysis of the driving behaviour will leak information about the systems controlling the vehicle, but the driving behaviour is unlikely to leak privacy of the passengers. To resolve other issues the movement of vehicles may be adjusted to arrive at a hub at the same time in order to synchronise the time at which pseudonyms are changed. Autonomy also facilitates cooperative driving of multiple vehicles. Within this context, the autonomy might remove some of the identifying behavioural information leaked while driving and enhance the location privacy [102].

E. LOCATION SHARING IN A MILITARY SCENARIO

Sharing location information among collaborating parties may be necessary in many cases. In an operation with multiple parties, each party might need to conduct computation based on the other's location information; however, none of them may be willing to give up their privacy. One of the most appropriate examples for this case are military operations consisting of allies who benefit from cooperation but do not wish to fully trust each other. For example, when multiple allies are proceeding to the same target they would like to know about each other's location to prevent friendly fire. Another scenario might be, where country A decides to attack a target x, however, A does not want to damage its relationship with its allies who have interests around x. None of the countries would like to disclose sensitive location information to each other and A would not like to disclose the exact location of x [103]. A vehicular scenario could involve allies needing to coordinate military vehicles, but also be unwilling to disclose their precise location. The question here is, how should a computation on the data from multiple owners be performed without disclosing information (such as location) intended to be private? One option is to use an external trusted third-party aggregator. Alternately, secure multi-party computation [104] can be used if a trusted third-party is unsuitable.

F. COST OF PRIVACY PRESERVING TECHNIQUES

In order to provide privacy there will be a cost associated with the technique used. This cost could occur in a number of ways, such as financial, temporal (such as delays in service), energy, efficacy (such as an approximate result), additional computation and communication overheads, and others. Furthermore, preserving privacy is likely to increase the complexity of the system making it harder to understand and thus leading to harder to uncover privacy issues.

When choosing which privacy preserving technique to apply, it is important to understand what the costs are. This is because there may be a variety of different techniques that could be applied, but only some will be suitable due to the costs. For example, in a vehicular system it is vital to ensure that that the system remains safe, therefore, a temporal privacy cost may be undesirable if it decreases safety due to an increased response time. It is important to consider when these costs are applied. For example, [62] introduces a silent period for CAMs after changing identity to prevent an adversary being able to link the old and new identities. As CAMs are used to provide safety context information, the technique only allows identity to change followed by a silent period when a vehicle is below a specific speed. Other techniques have restricted this further and apply identity change at stationary social spots such as intersections [24]. Therefore, a trade-off needs to be made between privacy and safety when choosing between techniques in this example.

To reduce the cost of privacy preserving techniques, it may be useful to consider applying other techniques to the problem. For example, in [63] a privacy preserving revocation system called SmartRevoc was presented which used parked vehicles to aid in the dissemination of certificate revocation lists. This technique could potentially apply [105] to reduce SmartRevoc's energy cost which proposed a VANET routing protocol also using parked vehicles. The benefit of this scheme is that the parked vehicles selected for routing takes the limited energy of these vehicles into account, ensuring they have sufficient power for later use. These parked vehicles are also only selected when there is insufficient traffic density to relay messages. However, the use of [105] to reduce the energy cost of the scheme must be analysed to understand the impact its use will have on vehicle privacy.

In summary, it is important to understand (i) the cost of applying a privacy preserving technique, (ii) cost differences between different techniques, and (iii) how non-privacy preserving techniques can be applied to privacy preserving techniques to reduce their costs.

VII. FUTURE WORK

In this section we discuss possible future work in protecting vehicle location privacy.

A. LOCATION PRIVACY AGAINST MULTIPLE SIMULTANEOUS THREATS

This work has argued that it is insufficient to consider protecting location privacy threats against vehicle in isolation. It is necessary to consider the wider privacy threat landscape, because the way privacy preserving techniques interact can lead to no privacy actually being provided. So when designing privacy preserving techniques, multiple threats need to be simultaneously considered.

As privacy provision must consider other privacy threats concurrently, another issue is how to coordinate the privacy provision between multiple devices. This could involve a central authority (such as the vehicle) being in control of how privacy techniques synchronise. Alternatively a consensus based protocol could be developed where multiple devices agree to synchronise privacy provision at specific times. A third alternative might be a reactive protocol where devices respond to changes in privacy techniques. Such techniques need to be carefully designed to ensure a threat actor cannot alter how privacy is provided. For future work, we plan to investigate protocols that allow a vehicle to negotiate aligning identity change (such as for V2X, WiFi and Bluetooth) with internal devices whilst continuing to preserve privacy.

This means it will no longer be sufficient to look at privacy in a single domain, but necessary to provide cross-domain privacy. Here, multiple sources of privacy leakages from different domains will need to collaborate to protect privacy. This may be difficult as technologies can evolve in unexpected ways (such as vehicles hosting WiFi access points). This collaboration will also need to occur in a way that does not leak privacy.

B. IMPACT ANALYSIS OF PRIVACY THREATS

When considering a privacy threat it is important to clearly understand which threat actor is being protected against. This includes understanding their motivations, resources, and capabilities. For each threat actor a risk assessment can then be performed to analyse the likelihood and impact of a threat actor violating privacy. The risk analysis can then be used to (i) identify changes that need to be made to the system to preserve privacy, (ii) identify which changes need to be focused on with a higher priority, and (iii) which privacy leakages to specific threat actors are acceptable (and do not necessarily need a privacy preserving technique implemented — e.g., eCall). When changes to the system are made the risk analysis can be re-performed to ensure that the likelihood of privacy loss and its impact have decreased. However, privacy provision is difficult to identify, as the interactions between privacy techniques can lead to unexpected privacy loss. The possibility for privacy preserving techniques failing to protect privacy needs to be addressed in a risk assessment.

VIII. CONCLUSION

There exists many ways in which a vehicle can be tracked, and much work has been done on individually addressing some issues. However, an issue with existing work is that it typically focuses on a specific problem and do not consider attempting to protect context information leakages from other sources. The conclusion from this work is that it is important to not consider vehicular location privacy in isolation, as location privacy schemes can be circumvented by simply using an alternate tracking method. As existing work mostly does not consider the impact of their privacy schemes on other privacy techniques, future techniques should investigate the interaction between multiple privacy-preserving techniques. For example, [87] is the only example known to the authors where two sources of privacy leakage are addressed simultaneously. One of the key points of the work, was the need to synchronise pseudonym and MAC slot changes. Such synchronisation will be needed across the privacy preserving techniques that use pseudonyms to prevent vehicle tracking.

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