Security and Privacy Issues for Connected Vehicles

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Abstract. Modern vehicles contain more than a hundred Electronic Control Units (ECUs) that communicate over different in-vehicle networks, and they are often connected to the Internet, which makes them vulnerable to various cyber-attacks. Besides, data collected by the connected vehicles is directly connected to the vehicular network. Thus, big vehicular data are collected, which are valuable and generate insights into driver behavior. Previously, a probabilistic modeling and simulation language named vehicleLang is presented to analyze the security of connected vehicles. However, the privacy issues of vehicular data have not been addressed. To fill in the gap, this work present a privacy specification for vehicles based on vehicleLang, which uses the Meta Attack Language (MAL) to assess the security of connected vehicles in a formal way, with a special focus on the privacy aspect. To evaluate this work, test cases are also presented.

Keywords: Vehicle security · Security metrics · Location privacy.

1 Introduction

Modern vehicles are becoming computers on wheels. They contain more than 100 ECUs, and each of them is responsible for one or more functions, e.g. brakes, steers, airbags. Besides, these ECUs are dependent highly on software, which is either made entirely by Original Equipment Manufacturers (OEMs), or uses a standardized software framework (e.g. AUTOSAR[1]). Moreover, they often connected to the Internet, thus they open to cyber-attacks.

Currently, connected vehicle processes up to 25 gigabytes of data an hour[2]. This could be welcome for insurance companies, as additional data will allow them to better tailor insurance policies to individual drivers. Besides, the vehicular data generate insights into driver behaviour, which helps vehicle manufacturers to better understand their customers, and develop new safety features. Besides, modern vehicles are often equipped with a Telematic Control

[1] https://www.autosar.org/
[2] https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/whats-driving-the-connected-car
Unit (TCU) that controls tracking of the vehicle. This TCU consists of a GPS
device and an external interface for mobile communication (e.g. cellular net-
work, WiFi). According to [16], GPS tracking data stored by GPS devices can
identify the actual positions of the vehicles successfully. Also, vehicle network
services provide users with location-based services (LBSs) including local news,
directions, points of interest, directory assistance and fleet management, which
also collect geolocation data of users. However, these data may contain sensitive
information about users [4]. If they are accessed by malicious attackers or un-
trusted network services, privacy issues will be raised, e.g., driving patterns will
be learned, and current location will be predicted. Therefore, vehicular data,
especially geolocation data, needs to be collected in a privacy-preserving way.

One approach to improve security and privacy of connected vehicles is threat
modeling, and the most recent trend is to couple it with attack simulations, to
provide probabilistic quantitative measures to security, e.g. Time-To-Compromise
(TTC) [5, 6]. Previously, MAL is proposed to serve as a framework to develop
domain specific attack languages. Based on which, vehicleLang is proposed to
design vehicles with respect to their IT infrastructure and analyze their weak-
nesses.

The remainder of the paper is as follows. Section 2 considers related work. In
Section 3, we describe the applied methodology. Section 4 presents test cases of
the designed language as evaluation. Finally, the paper is concluded and future
work is described in Section 5.

2 Related Work

This section is divided into four parts, first we show the core work in vehicle se-
curity, after which vehicle threat modeling methods are described, and vehicular
data privacy issues are addressed. Finally, the relevant privacy mechanism are
described.

2.1 Vehicle Security

Previously, vehicle OEMs did not consider cyber-attacks that much, since an at-
tack was only possible if an attacker had physical access to the vehicle. However,
as modern vehicles have multiple wireless connections to outside networks and
devices (e.g. bluetooth, Internet), attacks are dramatically increasing. Therefore,
identifying what could go wrong in a vehicle is important, both in a physical
view and a functional view [9].

According to the work by [10], the main assets in a vehicle include ECU,
GatewayECU, Network, Dataflow, Protocol and Software. Possible attack steps
and defenses of each asset were also shown in this work. For example, an attacker
who is connected to an ECU can try to get access to the ECU, exploit possible
connection vulnerabilities, compromise connect privileges, and attempt change
operation mode; a possible defense is preventing ECUs from entering diagnostics
mode after it has started moving. Besides, the work by [1] addressed the security
issues in the CAN protocol, including 1) lack of authentication, 2) lack of network segmentation, 3) lack of data encryption, and 4) vulnerable to denial-of-service (DoS) attacks.

Possible security mechanisms to secure vehicles internal communications were addressed by HoliSec[3] which include message authentication codes (MAC) for traffic integrity, firewalls both for external traffic and for internal traffic implemented in gateway ECUs, use of Intrusion Detection Systems (IDSs) to detect unusual activities on the networks, and certificates for identification of various devices. Security mechanisms were also addressed by [1] to mitigate the threats on assets, which include access control, packet filter firewall, message authentication, etc.

2.2 Vehicle Threat Modeling

Threat modeling is a process that can be used to analyze potential attacks and threats. It can be supported by threat libraries or attack taxonomies.

In the work by [8] they adapted two threat modeling methods from the computer industry, TARA and STRIDE, to fit the needs of the automotive industry. They also mentioned that with the development of Vehicle-to-X (V2X) technology and the autonomous driving, more threat modeling methods will be needed.

[11] proposed a "practical and efficient" approach to threat modeling, which extended the Threat Modeling Tool (TMT) to better fit the automotive systems. However, they have so far done a proof-of-concept implementation of their approach without further validation.

The process for automotive threat modeling proposed by [12] starts with first defining automotive security use cases, then identifying assets and threats by using the STRIDE method, and finally rating risks and evaluating the threat level and impact level against the found threats. The authors also claimed that threat modeling should be performed in all phases of the development life cycle.

Assessing exploitability risks of vehicular on-board networks via automatically generated and analyzed attack graphs was demonstrated by [14]. Their stochastic model and algorithm could aid vehicle development by automatically re-checking the architecture for attack combinations, which may be enabled by mistakes or not trivial to spot by the human developer.

[10] presented vehicleLang, which is a probabilistic modeling and simulation language for vehicular cyber-attacks, and can be used to design vehicles and analyze their weaknesses. It was designed based on the Meta Attack Language (MAL), which may be used to design domain-specific attack languages, and provides a formalism that allows semi-automated generation and efficient computation of very large attack graphs.

http://autosec.se/wp-content/uploads/2018/04/1.2-holisec-state-of-the-art.pdf
2.3 Vehicular Data Privacy

In order to analyze and protect vehicular data, we classify vehicular data into four data types (shown in Table 1).

Table 1. Vehicular data type.

| Data type       | Description                                                                 | Created from                                                                 | Stored at         |
|-----------------|-----------------------------------------------------------------------------|------------------------------------------------------------------------------|-------------------|
| Geolocation     | It can reveal an user’s movements in real time, as well as provide a detailed, comprehensive record of an user’s movements over time, usage of this sensitive data can raise privacy concerns. | 1) Telematics systems provided by vehicle manufacturers; 2) Location-based services provided by portable navigation devices and smart phones | TCU               |
| Vehicular sensor | Including intake air temperature, engine temperature, adapter voltage, CO₂ instant, fuel flow, speed and revolutions per minute (RPM) | In-vehicle sensors                                                          | ECU               |
| Biometrics      | Information about the physical or biological characteristics and traits of a driver, or biometrics, will present opportunities for new vehicle features in the future such as providing access controls or driver identification. | In-vehicle sensors                                                          | Biometric car access or identification system |
| Behavioral      | Information about the drivers attention, speed, steering and braking habits and combine this with other diagnostic data to provide new safety features. | In-vehicle data recorder                                                    | Within secure element in the vehicle, or potentially transmitted back to manufacturer servers |

As is shown in Table 1, geolocation data are sensitive and may raise privacy issues. One way to protect its privacy is to de-identify data, through removing certain identifiers e.g. the vehicle identification number (VIN) and the license plate from the dataset. However, a real-world example has shown that it may not always protect users against privacy risks, as some de-identification methods allow for a user to be re-identified. Except for geolocation data, no privacy-protection methods were found for other data types. Apart from these

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4 https://www.gao.gov/assets/660/659509.pdf
5 https://fpf.org/wp-content/uploads/
6 https://findbiometrics.com/biometric-vehicle-access-411029/
data types, dataflow in vehicles also needs to be secured. According to [10],
dataflow is a channel that contains data in transit, and can be classified into
connection oriented dataflow, and connectionless dataflow.

Therefore, in this work, we will take geolocation data as an example that we
would like to protect via efficient privacy mechanisms.

2.4 Privacy Mechanism

In order to protect the privacy of vehicular data, especially geolocation data,
we suggest geolocation data can be gathered under differential privacy [2], its
definition is as follows:

**Definition 1.** $\epsilon$-differential privacy. A randomized function $K$ gives $\epsilon$-differential
privacy if for all data sets $D_1$ and $D_2$ differing on at most one element, and all
$S \subseteq \text{Range}(K)$,

$$\Pr[K(D_1) \in S] \leq \exp(\epsilon) \times \Pr[K(D_2) \in S]$$

(1)

Differential privacy is essentially a noise perturbation mechanism. It pro-
vides a quantitative mathematical definition to measure the privacy level, and a
smaller $\epsilon$ indicates a larger noise amount, and a larger privacy level.

3 Methodology

3.1 Vehicle Main Assets and Associations

In this section, we aim to analyze the security of connected vehicles, as well as
their privacy issues. Thus, the first thing is to understand the internal network
of a vehicle, and the main assets in it. A short description of the main assets of
connected vehicles can be seen in Table 2.

| Asset       | Description                                                                 |
|-------------|------------------------------------------------------------------------------|
| ECU         | An ECU is responsible for one or more features/tasks of the vehicle. Each ECU can execute one or more Software but only one Firmware (which is also a type of Software), can have Data stored in it. |
| GatewayECU  | A GatewayECU is a specialization of an ECU that acts as a gateway on a vehicle connecting two or more VehicularNetwork, it has the option to activate a firewall and an IDPS to prevent certain attacks. |
| Network     | A Network includes VehicleNetwork (e.g. CAN, LIN, MOST and FlexRay) and Ethernet. |
| Data        | Data represent communication among Network, and can also be stored by ECU. |
| Software    | Software used on ECU is made by OEMs or used an existing architecture standard (e.g. AUTOSAR). |
In this work, we extend vehicleLang \cite{10} by adding Geolocation, Untrusted NetworkService and PrivateUser assets, and we call it priVehiLang.

Firstly, Geolocation extends Data and contains sensitive information about users. It is created from Telematics systems (PhysicalMachine). It is stored at ECU, or it can be uploaded to NetworkServices by users to use location-based services. Besides, a UntrustedNetworkService extends NetworkService and indicates a untrusted network service (e.g. LBS). Moreover, a PrivateUser extends User, which uses UntrustedNetworkServices, and also sets its privacy level. The UML diagram of assets and associations can be seen in Fig. 1.

![UML Diagram](image)

**Fig. 1.** Assets and associations UML diagram of priVehiLang.

### 3.2 The Meta Attack Language (MAL)

MAL can efficiently describe assets (e.g. Data), their instances (e.g. Geolocation), attack steps and defenses (e.g. Geolocation.access). Attack steps are connected to each other, and they may be of the type OR or AND, $t(X.A) \in \{OR, AND\}$. Besides, the successfully compromise of one step leads to the second step, for example,

$$(\text{Geolocation}.\text{access}, \text{Geolocation}.\text{read}) \in E,$$

Defenses are represented with the symbol $\#$ and assume boolean values to indicate their status. Technically, each defense includes an attack step. If the defense is false, then, at the time of instantiation, the associated attack step is marked as compromised.
3.3 Geolocation Data Attack Steps Description

According to the formalism of MAL, a short description of geolocation data and untrusted network service attack steps can be seen in Table 3.

| Attack step         | Attack type | Description                                                                 | Possible defense/Obstacle |
|---------------------|-------------|------------------------------------------------------------------------------|----------------------------|
| ecuAccess           | OR          | This a helper attack step. If ECU is accessed, the geolocation data stored in it can be directly accessed. | None                       |
| untrustedNetworkServiceAccess | OR          | This a helper attack step. If the network service is untrusted third party, geolocation data uploaded can be directly accessed. | None                       |
| access              | OR          | If the software is untrusted third party, location data can be accessed. | None                       |
| read                | OR          | If location data is read by an attacker, the comprehensive picture of an users activities, movements, and driving patterns will be revealed. | A private user can set privacy level of untrusted network services by using local differential privacy techniques. |

Moreover, for the UntrustedNetworkService, it can be access with attack type AND. It can lead to the location data uploaded be directly accessed. As a defense, local differential privacy will be applied by the UntrustedNetworkService, and its privacy level will be set by a PrivateUser. The privacy mechanism will be described in the next section.

3.4 Local Differential Privacy (LDP)

Differential privacy is essentially a noise perturbation mechanism. It provides a quantitative mathematical definition to measure the privacy level. However, this mechanism rely on a trusted server by adding noise to the collected data, and there may be potential attacks before the collected data reach the trusted party, which is a big issue in sensor networks and Internet of things (IoT) systems.

Therefore, for systems e.g. connected vehicles where there is untrusted data collector, or untrusted network services, it is possible to adding noise individually by applying differential privacy in the local setting (i.e. LDP). In this work, we will apply local differential privacy as a defense of Geolocation.read.
3.5 Privacy MAL-specification for Vehicles

In this section, we present a privacy MAL-specification for vehicles based on vehicleLang, and the simulation will be executed by the MAL compiler (to be done).

```java
category Privacy {
asset Geolocation extends Data
asset UntrustedNetworkService extends NetworkService
asset PrivateUser extends User
}
associations {
}
```

4 Evaluation

In this section, we will use test cases to check whether the actual results of our method matches the expected result. A test case is a instantiated scenario that represents a real-world scenario. In this report, test cases are written in Java, and we use the MAL specification to compile it into Java classes and use MAL compiler to execute it. The simulation will report the correctness of all the assumptions made in the test cases, which are divided into three main parts: 1) initialize assets, 2) define assets and 3) assertions.

Consider the scenario that connected vehicles have an ECU transmitting GPS data across in-vehicle networks to other ECUs. We assume that an attacker has physical access to the ECU, then geolocation data stored in it can be accessed directly. The sample test case is depicted in Fig. 2.

![Fig. 2](image)

**Fig. 2.** An attacker has access to an ECU, will have direct access to the geolocation data stored in it.

The MAL specification of this test case is as follows:

```java
public void testcase1() {
    // Testing ECU attacks on access with all defenses enabled.
    ECU ecu = new ECU();
    // Enabled operation mode and message confliction protection.
    Geolocation geolocation = new Geolocation();
    ecu.addLocationDataStorage(geolocation)
}
```
Consider another scenario that a private user is using an untrusted network service. If an attacker has access to the untrusted network service, she will get access to the uploaded geolocation data. If no defenses are applied here, geolocation data will be read directly. Therefore, as a defense of reading geolocation data, the private user can set privacy level of the untrusted network service, through local differential privacy mechanism.

The MAL specification of this test case when disabling LDP is as follows:

```java
public void testcase2() {
    Geolocation geolocation = new Geolocation();
    UntrustedNetworkService untrustedNetworkService =
        new UntrustedNetworkService("UntrustedNetworkService", false);
    untrustedNetworkService.addLocationData(geolocation);

    Attacker attacker = new Attacker();
    attacker.addAttackPoint(untrustedNetworkService.access);
    attacker.attack();
}
```

**Fig. 3.** An attacker has access to an untrusted network service, will get access to the uploaded geolocation data. While a private user can set the privacy level of the network service according to her needs.

The MAL specification of this test case when disabling LDP is as follows:

```java
public void testcase2() {
    Geolocation geolocation = new Geolocation();
    UntrustedNetworkService untrustedNetworkService =
        new UntrustedNetworkService("UntrustedNetworkService", false);
    untrustedNetworkService.addLocationData(geolocation);

    Attacker attacker = new Attacker();
    attacker.addAttackPoint(untrustedNetworkService.access);
    attacker.attack();
```
However, when we enabling LDP, the test case will look like this:

```java
public void testcase3() {
    ...
    new UntrustedNetworkService("UntrustedNetworkService", True);
    ...
    geolocation.read.assertCompromisedWithEffort();
}
```

To measure the effectiveness of the privacy mechanism applied on this scenario, we provide users three privacy levels. By enabling and disabling the local differential privacy, we calculate the global TTC for each case. An assumption is made in Table 4.

| Privacy level | Low  | Medium | High |
|---------------|------|--------|------|
| Enable LDP    | 10h  | 50h    | 100h |
| Disable LDP   | 5h   | 5h     | 5h   |

If the priVehiLang and the test cases can be compiled properly, this work will provide quantitative security metrics (i.e. TTC) for connected vehicles. This will foster vehicle manufacturers to improve its security and privacy according to the needs of their customers.

5 Conclusion and Future Work

This work shows that, MAL helps to evaluate the security and privacy of connected vehicles efficiently, and in a quantitative way. Also, the results of the work can foster vehicle manufacturers to improve its security and privacy according to the needs of their customers.

Future work includes providing more accurate probability distributions on each attack step, by using machine learning techniques.

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