A Digital Forensic Approach for Optimizing the Investigation of Hit-and-Run Accidents

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Abstract. We present a novel digital forensic approach that facilitates the investigation of hit-and-run accidents. Based on wheel speeds gathered by forensic data loggers, our approach provides a priority ranking of the suspects in order to optimize further investigations. For this, we propose two investigation steps to get key information about a suspect's trip. First, we analyze the likely traveled routes of a suspect to determine whether the suspect could have been at the accident location. Second, we analyze the driving behavior of the suspect in terms of aggressiveness, since aggressive driving behavior is a major reason for traffic accidents. Our evaluation with real driving experiments shows that our approach is suitable for analyzing likely routes and driving behavior in order to prioritize suspects in an investigation.

Keywords: Digital forensic approach · Hit-and-run accidents · Route reconstruction · Driving behavior · Driving maneuvers

1 Introduction

Today's vehicles are equipped with a variety of inertial sensors to gather vehicle data, enabling the development of digital forensic approaches to investigate crimes involving vehicles. In this context, vehicle data is used to provide digital evidence as a complement to physical evidence [21]. In digital forensic investigations, vehicle data is usually obtained from event data recorders (EDR) integrated in the vehicle [16]. An EDR stores vehicle data covering the time period shortly around an accident. In contrast, forensic data loggers enable continuous gathering of vehicle data from the Controller Area Network (CAN bus) [15,18]. This is beneficial because the entire trip can be considered in the investigation. Forensic data loggers store vehicle data in a manner suitable for forensic investigations by ensuring integrity, authenticity, etc. In the era of connected vehicles, it is also possible to store vehicle data in the cloud [18,25].

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In this paper, we focus on the digital forensic investigation of hit-and-run accidents, as the number of hit-and-run accidents increases steadily [24]. Attention to this type of accident is important because a hit-and-run often proves to be fatal, either as a result of the collision or because of refusing first aid [3,24]. Hit-and-run accidents are typically investigated using third-party information such as surveillance cameras or eyewitnesses [8].

As our contribution, we propose a novel digital forensic approach to optimize the investigation of hit-and-run accidents based on in-vehicle data[1]. Our approach comprises two investigation steps. First, we reconstruct and analyze the likely routes of a suspect to determine whether the suspect could have been at the accident location. Then, we analyze the suspect's driving behavior in terms of aggressiveness. For example, we determine whether the suspect engaged in aggressive driving maneuvers near the accident location. This is of particular interest as aggressive driving behavior is a leading cause of traffic accidents [22]. The result of both steps is a priority ranking of suspects that enables law enforcement agencies to optimize subsequent investigations. In case of a hit-and-run, the perpetrator's vehicle often has physical evidence of the accident. By ranking suspects, law enforcement agencies can focus on the likely perpetrators when there are several suspects. This minimizes the risk of covering up physical evidence by the perpetrator.

We use wheel speeds gathered by a forensic data logger in our approach, as the use of wheel speeds is advantageous over other data sources such as GPS or inertial measurement units (IMU). Wheel speeds are available on the CAN bus of contemporary vehicles because of the mandatory anti-lock braking system (ABS) [23]. Thus, our approach is potentially applicable to a large number of today's vehicles. Whereas not every vehicle is equipped with an IMU and GPS is not always available, e.g. when driving in tunnels. Furthermore, wheel speeds are preferable from a data protection and privacy point of view, as our approach shows that wheel speeds are the minimal data set adequate and required for the investigation of hit-and-run accidents. As a result, our approach is in line with the principle of data minimization as defined in the EU General Data Protection Regulation (GDPR) [10]. In addition, wheel speeds are less privacy-invasive than, for example, surveillance cameras or GPS. Unlike surveillance cameras, wheel speeds are focused on the individual and do not monitor several people on suspicion. When GPS data is used, the actual traveled route and all places visited during the trip are revealed. This is particularly problematic if an unauthorized third party gains access to the GPS data. In contrast, wheel speeds can only be used to reveal this information if the area in which the trip took place is known [28,29]. As this information is known in a hit-and-run accident, wheel speeds are suitable for our approach. Although law enforcement agencies can gain insight into the places a suspect might have visited, they cannot clearly determine which of the likely routes the suspect actually took if more than one route is found. Thus, our approach helps law enforcement agencies to focus on

[1] A preliminary stage of this research was presented as an extended abstract at the PerCom PhD Forum 2019 [27].

suspects at an early stage, and yet innocent suspects in particular do not need to disclose where they actually traveled.

The rest of this paper is organized as follows. We discuss related work in Sect. 2 and introduce our digital forensic approach in Sect. 3. Then, we present details about both investigation steps in Sects. 4 and 5. In Sect. 6, we demonstrate that the presented approach is well suited for investigating hit-and-run accidents. Finally, we conclude the paper in Sect. 7.

2 Related Work

In our digital forensic approach, we investigate hit-and-run accidents by analyzing likely traveled routes. Existing algorithms for the reconstruction of a driver's likely routes differ in the requirements for the reconstruction and the sensors used. Some approaches require the start and/or the end positions of the trip [11,13], while other approaches require knowledge of the area in which the trip took place [17,20,28,29]. Typically, accelerometer, gyroscope and/or magnetometer readings are used as input data [17,20]. A further way is to use the vehicle's velocity or wheel speeds [11,13,28]. In this paper, the investigation of likely routes is based on an algorithm that we developed in prior work [29]. This algorithm uses distances and turns to determine a driver's likely routes in a given urban area. Distances and turns can be calculated from wheel speeds [28]. An advantage of this algorithm is its robustness against distance and turn errors. Furthermore, the algorithm does not require any additional information about the traveled route besides the area in which the trip took place, e.g. no start and/or end position. Since the perpetrator might lie about his start/end positions, algorithms that require any additional information do not work in forensic approaches. In case of a hit-and-run accident, we know the accident location and adapt the algorithm to leverage this information.

Furthermore, we analyze driving behavior in our digital forensic approach. Most existing algorithms for assessing driving behavior require data from different sources, e.g. accelerometer, magnetometer and GPS [5,7,12]. In our approach, we only use wheel speed sensors as data source, resulting in a minimal data set as explained in Sect. 1. In prior work [30], we introduced a scoring algorithm to measure driving behavior while driving in a driver feedback system. This algorithm calculates acceleration characteristics from the vehicle's wheel speeds and determines the closeness of the driving behavior to a physically unsafe driving situation based on a safety domain introduced by Eboli et al. [12]. Our digital forensic approach, however, focuses on the retrospective analysis of the driving behavior of a suspect in terms of aggressiveness. For this, we introduce severity levels to categorize driving maneuvers at any point of the suspect's trip based on the findings of our prior work [30]. In addition, we incorporate another physical quantity in our behavioral analysis, namely the vehicle's jerk.

In terms of digital forensic investigations, Cebe et al. [8] presented a blockchain-based system for collecting and managing vehicle data and environmental data to address digital forensics for connected vehicles in smart cities with smart infrastructure such as traffic lights. They briefly discuss how to resolve hit-and-run accidents using their system, but only in the sense of recognizing a hit-and-run by proving that a vehicle has fled the accident scene. Our aim is to prioritize suspects for subsequent investigations if a hit-and-run accident has occurred. Furthermore, the approach of Cebe et al. is only designed for connected vehicles in a smart city. In contrast, our approach can potentially be used in a large number of today's vehicles by retrofitting forensic data loggers. The work of Hoppe et al. [15] is most related to our work. They presented a forensic route reconstruction approach using vehicle data gathered by a forensic data logger in order to provide digital evidence in hit-and-run accidents. However, this approach provides only manual or semi-automated route reconstruction. For manual route reconstruction, the vehicle's velocity is used to estimate the traveled distance. If a position of the trip is known, e.g. the start or end position, the traveled route can be manually reconstructed in the street network by plausibility checks, such as verifying whether the estimated distance is correct. For semi-automated route reconstruction, a hardware-based navigation system is used to simulate a trip and generate possible routes based on the gathered vehicle data. However, the semi-automated approach requires a suspected start position and manual configuration as well as interaction steps. Instead, our approach allows for a fully-automated route reconstruction. Al-Kuwari et al. [4] proposed a probabilistic algorithm based on Bayesian inference to reconstruct the likely routes of a suspect when parts of the route are known, e.g. from surveillance cameras and GPS. In contrast to Hoppe et al. and Al-Kuwari et al., we do not require any additional information about the traveled route apart from the already known accident location. This is crucial, as it makes us independent of the possibly untrue statements of the suspects. Finally, in contrast to the other approaches, we consider driving behavior in the investigation and thus advance the state of the art.

3 Digital Forensic Approach

In this section, we provide an overview of our digital forensic approach to optimize the investigation of hit-and-run accidents. In our approach, we assume the following scenario [15,27]: *A law enforcement agency is investigating a traffic accident in which a driver caused bodily injury and fled the accident scene (hit-and-run accident). In addition to the accident location, the law enforcement agency knows the approximate accident time and the vehicle model from eyewitness reports. Based on this information, the number of suspects can be reduced. The suspects' vehicles are equipped with forensic data loggers that continuously store vehicle data such as wheel speeds locally or in the cloud. The law enforcement agency asks the suspects to voluntarily provide the wheel speeds of the trips in question for forensic analysis, comparable to a voluntary DNA profiling in other criminal investigations. The law enforcement agency uses the wheel speeds to find indications of the suspects' involvement in the accident by applying the* *digital forensic approach presented in this paper. This enables the law enforcement agency to prioritize the suspects, e.g. to determine which suspects will be interrogated first.*

We follow the digital forensic process model of the German Federal Office for Information Security (BSI) [1], which is divided into different phases describing steps to be taken before, during and after a forensic investigation. This includes, for example, the installation of forensic data loggers in vehicles to enable continuous gathering and storing of wheel speeds from the CAN bus. Hoppe et al. [15] also applied this model to the investigation of automotive incidents. In this paper, we focus on the phases during a forensic investigation, i.e. the inspection and data analysis phases. The inspection phase involves calculating vehicle-related data from wheel speeds as preprocessing for the data analysis phase. During the data analysis phase, we investigate whether a suspect may have committed the hit-and-run. For more details about the process model, refer to the digital forensics guideline of the BSI [1]. In the following we describe the course of both phases in our digital forensic approach.

3.1 Inspection Phase

In the inspection phase, we use the wheel speeds to calculate vehicle-related data as preprocessing for the data analysis phase. We require a sampling rate of at least 1 Hz. Furthermore, the wheel speeds must be timestamped by a synchronized clock, as the data is used for forensic purposes. Otherwise, we cannot determine whether the vehicle of a suspect was driven during the time of the accident. However, this is a reasonable assumption, since the forensic data logger can be equipped with a radio clock or the time can be synchronized over the network if the wheel speeds are stored in the cloud.

We define a wheel speed measurement $\mathcal{W}(t)$ at time t as a tuple of right and left front wheel speeds $w_{\mathrm{rf}}(t)$ and $w_{\mathrm{lf}}(t)$ as well as right and left rear wheel speeds $w_{\mathrm{rr}}(t)$ and $w_{\mathrm{lr}}(t)$ (each in ms^{-1}):

$$\mathcal{W}(t) = (w_{\mathrm{rf}}(t), w_{\mathrm{lf}}(t), w_{\mathrm{rr}}(t), w_{\mathrm{lr}}(t)) \tag{1}$$

The vehicle's velocity $v(t)$ (in ms^{-1}) at time t can be estimated as the mean of the right and left rear wheel speeds $w_{\mathrm{rr}}(t)$ and $w_{\mathrm{lr}}(t)$ [6]:

$$v(t) = \frac{w_{\mathrm{rr}}(t) + w_{\mathrm{lr}}(t)}{2} \tag{2}$$

The first and second derivatives of the velocity $v(t)$ are the longitudinal acceleration $a_{\mathrm{lon}}(t)$ and the longitudinal jerk $j_{\mathrm{lon}}(t)$ respectively. The yaw rate $r(t)$ of a vehicle at time t can be estimated using the right and left rear wheel speeds $w_{\mathrm{rr}}(t)$ and $w_{\mathrm{lr}}(t)$ as well as the vehicle's rear track width $\mathcal{T}$ (in m) [6]:

$$r(t) = \frac{w_{\mathrm{rr}}(t) - w_{\mathrm{lr}}(t)}{\mathcal{T}} \tag{3}$$

Neglecting the sideslip angle, the vehicle's heading $\psi(t)$ at time t can be estimated by integrating the yaw rate $r(t)$ [9]:

$$\psi(t) = \int_0^t r(t)\, dt \tag{4}$$

The vehicle's lateral acceleration $a_{\text{lat}}(t)$ can be estimated using the velocity $v(t)$ and the yaw rate $r(t)$, neglecting the sideslip angle [9]:

$$a_{\text{lat}}(t) = v(t) \cdot r(t) \tag{5}$$

The derivative of the lateral acceleration $a_{\text{lat}}(t)$ is the lateral jerk $j_{\text{lat}}(t)$. The vehicle's orientation-independent total acceleration $\|a(t)\|$ is the magnitude of the acceleration vector $(a_{\text{lon}}(t), a_{\text{lat}}(t))$:

$$\|a(t)\| = \sqrt{a_{\text{lon}}(t)^2 + a_{\text{lat}}(t)^2} \tag{6}$$

Accordingly, the vehicle's total jerk $\|j(t)\|$ is the magnitude of the jerk vector $(j_{\text{lon}}(t), j_{\text{lat}}(t))$:

$$\|j(t)\| = \sqrt{j_{\text{lon}}(t)^2 + j_{\text{lat}}(t)^2} \tag{7}$$

3.2 Data Analysis Phase

For the data analysis phase, we propose two investigation steps: (1) investigating the likely routes of a suspect and (2) investigating the driving behavior of a suspect. In the first investigation step, we analyze whether a suspect could have been at the accident location based on the gathered vehicle data. In the second investigation step, we analyze the driving behavior of the suspects and determine which suspects tended to drive aggressively. Furthermore, we investigate whether a suspect performed extreme driving maneuvers, e.g. sudden braking or strong acceleration, near the accident location. We describe both investigation step in detail in Sects. 4 and 5.

Each investigation step provides a ranking of suspects. The smaller the rank of a suspect, the more likely he or she was involved in the accident according to our analysis. We merge the rankings of both investigation steps into a single priority ranking. The smaller the rank of a suspect in each ranking of the investigation steps, the smaller his or her rank in the resulting priority ranking (where a small rank means a high priority). Due to the prioritization of suspects, we do not risk dropping the perpetrator as a suspect. We suggest to consider high-ranked suspects first in subsequent investigations.

4 Investigating Likely Routes

The aim of investigating the likely routes of the suspects is to determine which of the suspects could have been at the accident location and should thus be considered as possible perpetrators. In the following, we first present the reconstruction of likely routes. Then, we describe how to analyze the likely routes of a suspect in an investigation.

4.1 Reconstruction of Likely Routes

In order to reconstruct the likely routes of a suspect, we use an algorithm that determines the likely routes of a driver in a given urban area using the distances and turns caused by traveling the route [29]. Distances and turns as a representation of a route are used, for example, in turn-by-turn navigation to guide travelers to their destination. The basic idea of the route reconstruction algorithm is to map the distances and turns onto the street network of the trip area using a dynamic programming-based approach, resulting in a list of likely routes [29].

However, mapping distances and turns onto the street network is error prone due to measurement errors [29]. In case of a hit-and-run accident, the measured distances may not exactly match the distances in the street network, e.g. due wheel spin caused by an emergency braking followed by strong acceleration. In terms of turns, a *false positive* (FP) turn error can occur when a turn was measured although there was no junction in the street network. This type of error can be caused, for example, by an evasive maneuver in an accident. A *false negative* (FN) turn error can occur when a turn was not measured although there was a junction in the street network, e.g. due to a very slight turn. As stated in Sect. 2, the route reconstruction algorithm is robust against distance and turn errors and thus suitable for the investigation of hit-and-run accidents. The algorithm allows for an absolute distance deviation of up to ϵ_d percent. The number of tolerable FP and FN turn errors is denoted as ϵ_{FP} and ϵ_{FP} respectively. The algorithm ranks the reconstructed likely routes according to their distance and turn errors. The smaller the rank, the more likely a reconstructed route is to match the traveled route [29].

Below, we first show how to calculate distances and turns from the vehicle-related data introduced in Sect. 3.1. Then, we present how to determine the urban area in which the likely routes are reconstructed.

Distances and Turns. We use the vehicle-related data introduced in Sect. 3.1 to calculate the distances and turns as input for the route reconstruction algorithm. A turning maneuver is characterized by a significant change in the vehicle's heading $\psi(t)$. We consider an absolute change in heading of 20° between two times t_i and t_j with $i < j$ as significant. This allows for the recognition of turning maneuvers with interruptions, e.g. due to oncoming traffic. However, to minimize the chance of classifying a lane change or a slight curve as a turn, there must be an absolute change in heading of at least 10° within a single time step [20]. If the heading change is positive, the vehicle is turning *left*. A turn is also considered to be a *U-turn* if the positive heading change exceeds 160°. If the heading change is negative, the vehicle is turning *right*. We approximate the distance traveled between two consecutive turns by integrating the vehicle's velocity $v(t)$ over time.

Trip Area. The algorithm is capable of reconstructing likely routes in urban areas of about 1200 km^2, as we demonstrated in prior work [29]. A hit-and-run accident, however, provides information that can be used to significantly narrow down the area in which the perpetrator must have been driving (referred to as *trip area*). We use the accident location and the total distance d of a suspect's trip (in km) to approximate the trip area as a rectangle on the street network map with the accident location at the center. The street network is modeled as a graph. Streets and parts of streets are vertices (also referred to as *segments*) and turns between these streets are edges [29]. The trip area is bounded by the geographic coordinates (ϕ^-, λ^-) and (ϕ^+, λ^+), where ϕ denotes the latitude and λ the longitude (both in rad). Given the geographic coordinates of the accident location (ϕ_a, λ_a) in rad and the earth radius R in km, the bounding coordinates (ϕ^-, λ^-) and (ϕ^+, λ^+) are calculated as follows [19]:

$$\phi^- = \phi_a - \frac{d}{R}, \quad \phi^+ = \phi_a + \frac{d}{R} \tag{8}$$

$$\lambda^- = \lambda_a - \arcsin(\frac{\sin(\frac{d}{R})}{\cos(\phi_a)}), \quad \lambda^+ = \lambda_a + \arcsin(\frac{\sin(\frac{d}{R})}{\cos(\phi_a)}) \tag{9}$$

The trip area includes all locations within a distance d from the accident location [19]. Thus, the trip area includes all locations to which the perpetrator could have traveled from the accident location after committing the accident.

4.2 Analysis of Likely Routes

By analyzing the likely routes of a suspect, we address the question:

Did the suspect take a route that leads through the accident location?

In prior work [29], we found that the traveled route is among the 10 best ranked likely routes in 97% cases if no turn errors occurred. However, the probability does not increase significantly if more than 10 likely routes are considered. Thus, we suggest to consider the 10 best ranked likely routes in the analysis. However, it is not our goal to determine the exactly traveled route of a suspect. In our hit-and-run scenario, it is sufficient to show that a suspect could have been at the accident location.

To determine which suspects are likely to have driven along the accident location, we introduce a score s for the accident location. The higher the number of likely routes that include the accident location, the higher the score. In addition, the score is the higher, the better these likely routes are positioned among the 10 best ranked likely routes. A suspect is more likely to have driven along the accident location if the accident location has a comparatively high score. To calculate the score for a suspect, we first need the ranking position of each likely route among the 10 best ranked likely routes (denoted as p). The set P contains the ranking positions p of all likely routes that include the accident location. Using the ranking positions P, the score s of the accident location is calculated as follows:

$$s = \begin{cases} 0 & \text{if the accident location is not on a likely route} \\ \sum\limits_{p \in P} \frac{1}{p} & \text{otherwise} \end{cases} \tag{10}$$

If there is a likely route among the 10 best ranked likely routes that includes the accident location, the score of the accident location is greater than 0, indicating that the suspect could have been at the accident location. Since we consider the 10 best ranked likely routes, the maximum score is about 2.93, meaning that the accident location is located on all of the 10 likely routes.

For the trip of each suspect, we determine the 10 best ranked likely routes and calculate the score of the accident location. We rank the suspects according to their scores in descending order. In the resulting ranking, the suspect at position 1 has most likely driven along the accident location. Accordingly, the higher the rank of a suspect, the less likely it is that the suspect drove along the accident location.

5 Investigating Driving Behavior

By investigating the driving behavior of the suspects, we aim to find out which of the suspects tended to drive aggressively during the trip in question and in particular near the accident location. In the following, we first introduce the assessment of the severity of driving maneuvers. Then, we describe how the driving behavior of suspects can be analyzed based on the severity of driving maneuvers.

5.1 Severity of Driving Maneuvers

We introduce the following severity levels with numerical values for assessing driving maneuvers (in ascending order): *not severe (1)*, *low (2)*, *medium (3)*, *high (4)*, and *extreme (5)*. Since the wheel speed measurements are a time series (see Sect. 3.1), we can assign one of the severity levels to each time t of the trip. The severity level of the driving maneuver performed at time t is determined using the vehicle's total acceleration and total jerk as introduced in Sect. 3.1. First, we calculate an individual severity level for each of the two aforementioned quantities, resulting in two possible severity levels for time t. Then, we assign the maximum of these two possible severity levels to the time t as the severity level of the driving maneuver performed at time t. As a result, we have a severity level for each time t of the trip in question.

Total Acceleration. We use the vehicle's total acceleration $\|a(t)\|$ (see (6)) to determine the severity of driving maneuvers. The advantage of using the total acceleration is that it is composed of longitudinal and lateral acceleration. Thus, the total acceleration covers three components (acceleration, braking and turning) that are sufficient to represent all types of driving maneuvers [26].

In order to determine the severity of driving maneuvers, we utilize a threshold $\theta_{v(t)}$ introduced by Eboli et al. [12]. This threshold is based on physical limitations of vehicle dynamics and depends on the velocity of the vehicle. The threshold $\theta_{v(t)}$ (in ms^{-2}) is calculated with the vehicle's velocity $v(t) \leq 150\,\mathrm{km\,h}^{-1}$ as

Table 1. Conditions for determining the severity of a driving maneuver based on the total acceleration $\|a(t)\|$ and the total jerk $\|j(t)\|$.

Conditions for $\|a(t)\|$	Conditions for $\|j(t)\|$	Severity of maneuver (numerical value)
$\|a(t)\| < 0.3 \cdot \theta_{v(t)}$	$\|j(t)\| < 2$	*not severe (1)*
$0.3 \cdot \theta_{v(t)} \leq \|a(t)\| < 0.53 \cdot \theta_{v(t)}$	$2 \leq \|j(t)\| < 4.67$	*low (2)*
$0.53 \cdot \theta_{v(t)} \leq \|a(t)\| < 0.77 \cdot \theta_{v(t)}$	$4.67 \leq \|j(t)\| < 7.33$	*medium (3)*
$0.77 \cdot \theta_{v(t)} \leq \|a(t)\| < \theta_{v(t)}$	$7.33 \leq \|j(t)\| < 10$	*high (4)*
$\theta_{v(t)} \leq \|a(t)\|$	$10 \leq \|j(t)\|$	*extreme (5)*

follows:

$$\theta_{v(t)} = g \cdot \left[0.198 \cdot \left(\frac{v(t)}{100}\right)^2 - 0.592 \cdot \frac{v(t)}{100} + 0.569\right], \tag{11}$$

where g is the gravitational acceleration on Earth [12]. However, the threshold is only defined for velocities up to $150\,\mathrm{km\,h^{-1}}$ [12]. Thus, we calculate the threshold with $v(t) = 150\,\mathrm{km\,h^{-1}}$ for velocities greater than $150\,\mathrm{km\,h^{-1}}$.

If the total acceleration $\|a(t)\|$ exceeds the threshold $\theta_{v(t)}$, the severity of the driving maneuver is *extreme* because it is physically unsafe to drive the vehicle under these conditions [12]. On the other hand, driving is safe if the total acceleration is below the threshold $\theta_{v(t)}$ [12]. To have a more fine-grained assessment of the severity, we introduce the conditions listed in Table 1 to determine the severity of a driving maneuver based on the total acceleration $\|a(t)\|$. Assuming that a hit-and-run accident leads to a total acceleration close to or above the threshold $\theta_{v(t)}$, we set the limit for *extreme* severity to 100% of the threshold $\theta_{v(t)}$ to reflect an unsafe driving condition. In prior work [30], we found a total acceleration of less than 30% of the threshold $\theta_{v(t)}$ to be a suitable indicator for non-aggressive driving behavior. Thus, we set the limit for *low* severity to 30%. The remaining limits are evenly distributed between these boundaries.

Total Jerk. We also use the vehicle's total jerk $\|j(t)\|$ to determine the severity of driving maneuvers. In terms of driving comfort, a total jerk of $1\,\mathrm{ms^{-3}}$ is considered comfortable and a total jerk of $2\,\mathrm{ms^{-3}}$ is still acceptable [31]. In extreme situations, however, the total jerk can exceed $10\,\mathrm{ms^{-3}}$ [31]. We introduce the conditions specified in Table 1 to determine the severity of a driving maneuver based on the total jerk $\|j(t)\|$. We set the limit for *low* severity to $2\,\mathrm{ms^{-3}}$, as this is still an acceptable value for the total jerk. Based on Wei et al. [31], we set the limit for *extreme* severity is set to $10\,\mathrm{ms^{-3}}$. The remaining limits are evenly distributed between these boundaries.

5.2 Analysis of Driving Behavior

In this section, we introduce the use of the severity levels to analyze the driving behavior of a suspect with respect to the following questions:

1. Did the suspect drive aggressively?
2. Did the suspect perform risky driving maneuvers near the accident location?

To answer the first question, the likely routes found in the first investigation step are not required. Thus, the investigation of this question is independent of the first investigation step and can be addressed even if no likely routes were found. For the second question, however, we use the likely routes. A suspect may have been involved in the hit-and-run accident if the driving behavior of the suspect was aggressive or the suspect performed risky driving maneuvers near the accident location.

Did the Suspect Drive Aggressively? As stated in Sect. 5.1, at any time t of the suspect's trip, we have the severity level of the driving maneuver performed at time t. Using this information, we can assess the aggressiveness of suspects by evaluating the expected severity level of each suspect's trip.

Let X represent the severity level $l \in \{not\,severe, low, medium, high, extreme\}$ of a driving maneuver performed a time t within a suspect's trip. The possible values of X are $1, 2, 3, 4, 5$ for the severity levels *not severe*, *low*, *medium*, *high* and *extreme* (see Sect. 5.1). Within the trip of a suspect, the severity levels l occur with the empirical probabilities f_l. We calculate the severity rating r of a suspect's trip as the expected value of X as follows:

$$r = E[X] = f_{not\,severe} + 2 \cdot f_{low} + 3 \cdot f_{medium} + 4 \cdot f_{high} + 5 \cdot f_{extreme} \qquad (12)$$

The more the distribution of severity levels shifts towards the extreme level, the higher the rating. Therefore, a higher rating means a more aggressive driving behavior during the trip.

By sorting the suspects in descending order according to the severity ratings, we obtain a ranking that expresses the aggressiveness of the suspects relative to each other. The position in the ranking is related to the possible involvement in the hit-and-run accident, because aggressive driving increases the risk of accidents [2]. The smaller the rank of a suspect in the aggressiveness ranking (due to a high severity rating), the more aggressive the driving behavior was compared to the other suspects. However, the perpetrator may have a high rank if other suspects have driven more aggressively. For documentation purposes, we suggest to depict the severity ratings of all suspects in descending order to illustrate the aggressiveness ranking.

Did the Suspect Perform Risky Driving Maneuvers Near the Accident Location? Although the approximate accident time is known in our scenario (see Sect. 3), we refrain from using this information in answering the question whether a suspect performed risky driving maneuvers such as sudden braking or strong acceleration near the accident location. The time period in which the accident happened could be long and cover a large part of the trip. Consequently, the approximate accident time is not a suitable information to investigate the question addressed in this section. In contrast, the accident location is typically precise.

We use the likely routes found in the first investigation step to determine whether a suspect performed risky driving maneuvers near the accident location, i.e. maneuvers with high or extreme severity. Each of the likely routes that includes the accident location provides a point in the suspect's trip where the accident could have occurred. For each of these likely routes, we can determine the presence of risky driving maneuvers at the point where the accident could have occurred, as we are able to determine the severity level of a suspect's driving maneuver at any point of a trip (see Sect. 5.1). The presence of risky maneuvers near the accident location for any of the likely routes is an indication of an accident. We use this information to refine the aggressiveness ranking obtained in Sect. 5.2 by positioning all suspects with risky driving maneuvers near the accident location above those without risky driving maneuvers near the accident location.

For documentation purposes, the numerical values of the severity levels, i.e. $1, 2, 3, 4, 5$ for *not severe*, *low*, *medium*, *high* and *extreme*, can be plotted against distance traveled. Using this figure, risky driving maneuvers near the accident location can be easily identified.

6 Evaluation

In the following, we evaluate our digital forensic approach. First, we describe the data sets used in the evaluation. Then, we evaluate the investigation of likely routes and the investigation of driving behavior as presented in Sects. 4 and 5. Finally, we outline how to use our digital forensic approach in an investigation.

6.1 Data Sets

We collected two data sets to evaluate the investigation steps. Both data sets include wheel speeds gathered while driving a Ford C-Max. The wheel speeds were recorded at 100 Hz by a Raspberry Pi 2 connected to the vehicle's CAN bus. However, we sample the wheel speeds down to 1 Hz as this is sufficient for our approach. Below we briefly describe the characteristics of each data set.

Data Set 1. We performed a total of eight trips with different driving behavior in the urban area of Duisburg in Germany to create our first data set (referred to as data set D_1). Besides the wheel speeds, we also gathered GPS data as ground truth. We use this data set in the evaluation of both investigation steps.

First, we let the two drivers A and B drive the same route in a calm manner (referred to as *calm trips*). The route of these trips consists of 13 turns and has a total distance of about 3.5 km. For both drivers, we measured these 13 turns and thus have no turn errors. Then, both drivers drove the route again in a considerably more aggressive manner (referred to as *aggressive trips*). We measured 14 turns for driver A and 12 for driver B. Thus, we have one *FP* turn error for driver A and one *FN* turn error for driver B. A few weeks before, the two drivers drove a comparable route in a normal manner, i.e. without any instruction regarding the driving behavior (referred to as *normal trips*). The route of these two trips consists of 13 turns and has a total distance of about 4 km. For driver A, we measured 14 turns, i.e. we have one *FP* turn error. We measured 13 turns for driver B. Finally, the two drivers drove around the university building once each and performed an emergency braking followed by strong acceleration as typical maneuvers in hit-and-run accidents (referred to as *accident trips*). The route of these two trips consists of four turns and has a total distance of about 625 m. We measured four turns for both drivers A and B.

Data Set 2. To create our second data set (referred to as data set D_2), a driver performed three driving maneuvers that are common in accidents: emergency braking, evasive maneuver and change of direction [14]. We use this data set in the evaluation of the second investigation step. We instructed the driver to perform each maneuver three times with increasing aggressiveness, i.e. from *low* to *medium* to *high* aggressiveness.

6.2 Investigation of Likely Routes

In this section, we evaluate the first investigation step. This investigation step addresses the question *"Did the suspect take a route that leads through the accident location?"* and provides a ranking of suspects, expressing which suspects most likely drove along the accident location (see Sect. 4.2). We evaluate this investigation step using the trips from the data set D_1.

Throughout the evaluation, we consider two cases: 1) the suspect drove along the accident location and 2) the suspect did not drive along the accident location. The suspects of the first case are potential perpetrators and should be positioned at the top of the ranking, whereas the suspects of the second case are innocent should be positioned at the bottom of the ranking. We analyze the risk of considering potential perpetrators as innocent and innocent suspects as potential perpetrators. In addition, we analyze the risk that potential perpetrators will be at the bottom of the ranking and innocent suspects at the top.

In the following, we first provide the algorithm parameters used in our evaluation as well as information about the trip areas of data set D_1. Then, we present the results of the evaluation with regard to the two cases mentioned above.

Algorithm Parameters and Trip Area. For each trip of data set D_1, we determine the 10 best ranked likely routes as suggested in Sect. 4.2. We set the tolerable distance error ϵ_d to 15% [29]. We determine the number of tolerable *FN* and *FP* turn errors ϵ_{FN} and ϵ_{FP} depending on the number of measured turns, resulting in a turn error tolerance that is comparable to the distance error tolerance. If n turns were measured, we calculate ϵ_{FN} and ϵ_{FP} using the method of round half away from zero (denoted as $\lfloor\,\rceil$):

$$\epsilon_{\mathrm{FN}} = \epsilon_{\mathrm{FP}} = \lfloor 0.15\, n \rceil \tag{13}$$

Table 2. Parameters of the route reconstruction algorithm as well as information about the trip area for each trip in data set D_1. The road density is the ratio of the length of the area's road network (in km) to the area's size (in km^2).

Trip	Driver	ϵ_{FN}	ϵ_{FP}	Size of trip area	Road density
Calm	A	2	2	65.9 km^2	10.7
Calm	B	2	2	66.1 km^2	10.7
Normal	A	2	2	86.7 km^2	10.6
Normal	B	2	2	86.4 km^2	10.6
Aggressive	A	2	2	65.8 km^2	10.7
Aggressive	B	2	2	65.9 km^2	10.7
Accident	A	1	1	2.1 km^2	20.5
Accident	B	1	1	2.1 km^2	20.7

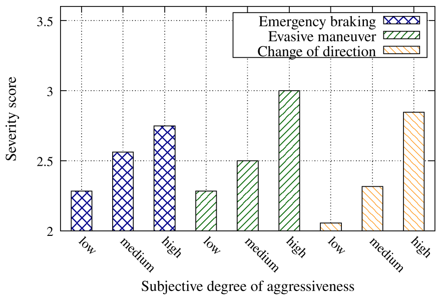
In an investigation, we would use the accident location to determine the trip area in which the perpetrator must have been driving (see Sect. 4.1). However, the trips of data set D_1 do not include real accidents. Thus, we use the central point of each trip to determine the respective trip area instead. For each segment in the trip area, we assume that an accident has happened on this segment, which leads to a complete analysis of the trip area. We calculate the central point of the trip as the coordinate (ϕ_c, λ_c) using the latitudes ϕ and longitudes λ of the trip:

$$(\phi_c, \lambda_c) = (\frac{\min(\phi) + \max(\phi)}{2}, \frac{\min(\lambda) + \max(\lambda)}{2}) \qquad (14)$$

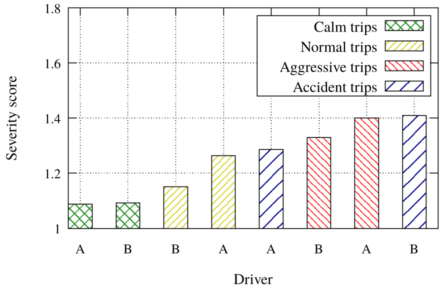
Using this central coordinate and the total distance of the respective trip, we determine the bounding coordinates of the trip area as described in Sect. 4.1. However, we increase trips's total distance by 15% to account for any distance errors. Table 2 provides the tolerable FN and FP turn errors ϵ_{FN} and ϵ_{FP} as well as information about the trip area for the trips from data set D_1.

Case: The Suspect Drove Along the Accident Location. We estimate the risk of considering a potential perpetrator as innocent to be low. For all trips from data set D_1, the traveled route is among the 10 best ranked likely routes with ranking positions between 1 and 6. As a result, we would have considered all drivers from data set D_1 as possible perpetrators if the accident had happened on the traveled routes.

Moreover, we estimate the risk of positioning potential perpetrators at the lower end of the ranking to be low. In contrast, potential perpetrators are likely to be put at the top of the ranking of the first investigation step. Among the likely routes, segments located on the traveled route have on average a higher score than segments that are not located on the traveled route (2.27 vs. 0.42). Thus, all drivers of data set D_1 would be positioned at the top of the ranking if the accident had happened on a segment located on their traveled routes.



(a) Common accident maneuvers



(b) Trips from data set D_1

Fig. 1. (a) Shows the severity ratings of common accident maneuvers (emergency braking, evasive maneuver and change of direction) from data set D_2 performed with increasing aggressiveness (*low*, *medium*, *high*). The severity rating increases with increasing aggressiveness. (b) Shows the severity ratings of the trips from data set D_1. The severity ratings are sorted in ascending order. The severity ratings correctly represent the respective driving behavior.

Case: The Suspect Did Not Drive Along the Accident Location. Overall, we estimate the risk of considering an innocent suspect as a potential perpetrator to be low, since for the trips from data set D_1 on average only 0.4% of all segments in the trip area are located on a likely route, but not on the traveled route. However, for an innocent suspect to be considered a potential perpetrator, an accident must have happened on one of these segments.

We estimate the risk of considering an innocent suspect as a potential perpetrator to be highest if the suspect's traveled route is short and common in urban areas. The route of the accident trips is short and less unique in the trip area than the routes of other trips. For the accident trips, the proportion of segments that could lead to considering an innocent suspect as a potential perpetrator is higher than for the other trips, namely 6.8%, leading to an increased risk.

Finally, we estimate the risk of positioning innocent suspects at the top of the ranking to be low. Overall, most segments that are located on a likely route, but not on the traveled route, have a comparatively low score with a mean value of 0.42. Thus, all drivers of data set D_1 are likely to be positioned at the bottom of the ranking if an accident had occurred on one of these segments. In contrast, potential perpetrators are likely to be positioned above the innocent suspects as we found in Sect. 6.2.

6.3 Investigation of Driving Behavior

In the following, we evaluate the second investigation step. In this investigation step, we rank the suspects according to the aggressiveness of their driving behavior. Furthermore, we determine the presence of risky driving maneuvers near the accident location to refine the ranking.

Aggressiveness of Driving Behavior. In this section, we evaluate the severity rating introduced in Sect. 5.2. The severity rating is used to address the question *"Did the suspect drive aggressively?"* phrased in Sect. 5.2.

Severity of Driving Maneuvers. First, we evaluate whether the severity rating can be used to distinguish between different degrees of severity of driving maneuvers. This is the fundamental prerequisite for the analysis of the driving behavior of a suspect during his or her entire trip. We use the common accident maneuvers (emergency braking, evasive maneuver and change of direction) from data set D_2 that were performed with increasing aggressiveness (*low*, *medium*, *high*).

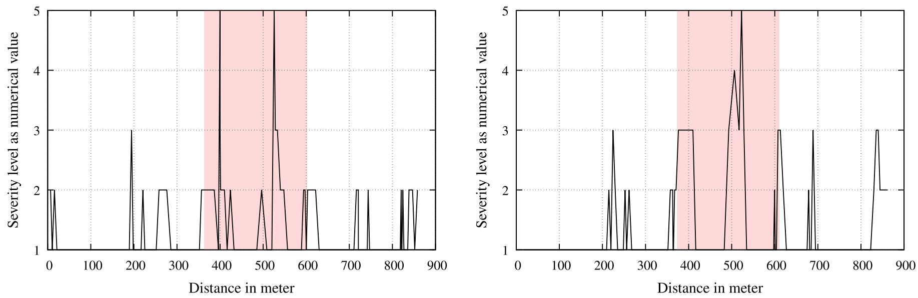
For each of the accident maneuvers, we calculate the severity rating as defined in (12). The results are illustrated in Fig. 1(a). For each accident maneuver, the severity rating is higher, the higher the aggressiveness with which the accident maneuver was performed. Thus, we conclude that the severity rating can be used to distinguish between different degrees of severity of driving maneuvers. For the emergency braking, the severity rating increases from 2.29 to 2.75 when increasing the subjective degree of aggressiveness from *low* to *high.* The severity ratings of the evasive maneuvers with a *low*, *medium* and *high* degree of aggressiveness are 2.29, 2.5 and 3 respectively. For the change of direction maneuver, the severity rating increases from 2.06 to 2.85 as the degree of aggressiveness is raised from *low* to *high.*

Assessment of Driving Behavior. Next, we evaluate whether the severity rating-based ranking expresses the aggressiveness of the suspects relative to each other. Here, we consider the entire trips of the suspects. We use the eight trips from data set D_1. These trips include calm, normal and aggressive driving behavior as well as accident maneuvers.

We calculate the severity rating for each trip and sort the trips according to their severity ratings, resulting in a ranking of the drivers. The results are shown in Fig. 1(b). Overall, the severity ratings are in line with the ground truth of our data set, as the severity ratings of the calm and normal trips are lower than the ratings of the aggressive and accident trips. Hence, the severity rating increases with increasing aggressiveness of the driver. We conclude that the severity rating is suitable for representing different kinds of driving behaviors. Furthermore, the ranking of the trips expresses the aggressiveness of the drivers relative to each other and can thus be used to rank the suspects in an investigation as described in Sect. 5.2.

Presence of Risky Driving Maneuvers. In the following, we evaluate whether our approach can be used to determine the presence of risky driving maneuvers such as sudden braking or strong acceleration within a trip. This information is used to address the question *"Did the suspect performed risky driving maneuvers near the accident location?"* phrased in Sect. 5.2.

We use the two accident trips from data set D_1, in which the drivers performed a common accident maneuver, i.e. emergency braking followed by strong



(a) Driver A's accident trip (b) Driver B's accident trip

Fig. 2. Severity levels plotted as numerical values (1, 2, 3, 4, 5 for *not severe*, *low*, *medium*, *high* and *extreme*). For both trips, there are extreme driving maneuvers when the accident maneuver was performed (highlighted in red). (Color figure online)

acceleration, after the second turn (see Sect. 6.1). For each trip, we rate the driving maneuvers as described in Sect. 5.1, resulting in a severity level for each time step of the trip. Figure 2 shows the severity levels of the driving maneuvers plotted as numerical values against the distance traveled as suggested in Sect. 5.2. The distance ranges in which the accident maneuvers were performed are highlighted in red. For both drivers, there are risky driving maneuvers with high and/or extreme severity in the respective distance range. As a result, there are indications of potential accidents in both trips. This demonstrates that our approach is well suited to discover risky driving maneuvers at a certain position of the route, e.g. near the accident location.

6.4 Using the Digital Forensic Approach in an Investigation

Here, we briefly outline how our digital forensic approach can be used in an investigation. We use data set D_1 and assume that the trips from data set D_1 were performed by different suspects. Furthermore, we assume that the accident happened at the location where the accident maneuvers of the accident trips were performed (see Fig. 2). Thus, the perpetrator is among the drivers of the accident trips and we expect these drivers to be positioned at the top of the priority ranking.

First, we analyze the likely routes of the suspects, resulting in a first ranking of suspects. The score of the accident location for the drivers of the normal and the accident trips are higher than for the other drivers, as these trips include the accident location. However, the score for the normal trips is higher than the score for the accident trips. Thus, the drivers of the normal trips are positioned above the drivers of the accident trips. The other drivers are positioned behind the drivers of the normal and the accident trips.

Next, we analyze the driving behavior, resulting in a second ranking of suspects. Figure 1(b) shows the ranking of the suspects based on the severity rating of their trips. The drivers of the aggressive and the accident trips are ranked above the other drivers. As Fig. 2 shows, there are risky driving maneuvers with high and/or extreme severity near the accident location for both accident trips, whereas there are no such maneuvers for the other trips. Thus, we can refine the ranking shown in Fig. 1(b), resulting in drivers of the accident trips being ranked above the drivers of the other trips.

We combine both aforementioned rankings into a single priority ranking. In the first ranking, the drivers of the accident trips are ranked at positions 3 and 4 and in the second ranking at positions 1 and 2. Finally, these suspects are positioned at the top of the final priority ranking and are prioritized in subsequent investigations.

7 Conclusion

We presented a novel digital forensic approach for optimizing the investigating hit-and-run accidents. For data protection and privacy reasons our approach is solely based on wheel speeds. This data is easy to gather if the vehicles are equipped with forensic data loggers and is available even when GPS is not, e.g. in tunnels or between tall buildings. We analyze the wheel speeds to identify the following key information about a suspect and his or her trip:

1. The possibility that a suspect took a route that led him or her through the accident location.
2. An analysis of the driving behavior of a suspect in terms of aggressiveness compared to the other suspects.
3. A rating of the driving behavior near the accident location to determine whether the suspect engaged in aggressive and risky driving maneuvers.

Based on this information, law enforcement agencies can prioritize suspects for subsequent investigations. This allows to focus on suspects which have most likely traveled along the accident location and had a suspicious driving behavior. This could make investigations more efficient and minimize the risk of covering up physical evidence. In contrast to GPS analysis, our approach only generates a list of likely routes that the suspect could have taken. For innocent suspects this implies that their whereabouts cannot be exactly identified, but law enforcement agencies can assign a low priority to them nonetheless.

For future work, we suggest to extend our approach by determining whether a suspect was actually driving the vehicle during the trip in question or whether another person was driving the vehicle. Future work could also investigate whether the driving behavior of a suspect became aggressive at a certain point, e.g. by fleeing quickly from the accident location.

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