Safety Challenges for Autonomous Vehicles in the Absence of Connectivity

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**Abstract**

Autonomous vehicles (AVs) are promoted as a technology that will create a future with effortless driving and virtually no traffic accidents. AV companies claim that, when fully developed, the technology will eliminate 94% of all accidents that are caused by human error. These AVs will likely avoid the large number of crashes caused by impaired, distracted or reckless drivers. But there remains a significant proportion of crashes for which no driver is directly responsible. In particular, the absence of connectivity of an AV with its neighboring vehicles (V2V) and the infrastructure (I2V) leads to a lack of information that can induce such crashes. Since AV designs today do not require such connectivity, these crashes would persist in the future. Using prototypical examples motivated by the NHTSA pre-crash scenario typology, we show that fully autonomous vehicles cannot guarantee safety in the absence of connectivity. Combining theoretical models and empirical data, we also argue that such hazardous scenarios will occur with a significantly high probability. This suggests that incorporating connectivity is an essential step on the path towards safe AV technology.

**1 Introduction**

With the introduction of autonomous vehicle (AV) technology, the vision of a safe transportation system with effortless driving seemed within reach. The vision captured the imagination of both venture capitalists and established automobile companies. Within just three years from August 2014 to June 2017 the AV industry attracted more than $80 billion dollars [13], so over the decade at least $100 billion dollars have been invested, exceeding the cost of the Apollo program. The AV companies are all pursuing the same goal: to develop a *fully autonomous* vehicle that does not

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communicate with either infrastructure or neighboring vehicles in order to function safely [3]. In 2012, Google co-founder Sergey Brin predicted AVs will be widely available in five years, and AV companies shared the belief that the goal would be realized by 2020 [3,14,18]. But in 2020 the goal seems out of reach. John Krafcik, the CEO of Waymo, recently declared that full autonomy may never be achieved [10]. Kyle Vogt, the President and CTO of Cruise, argued that in urban driving an AV must be able to hand off control to a human safety driver [31]. But the requirement of a safety driver drastically undermines the AV business case.

The general consensus now seems to be that if full autonomy is to be achieved, it is decades away [12]. Over time, the overwhelming complexities involved in urban driving have become apparent. In order to be safe, the AV needs to routinely navigate through out-of-the-ordinary road conditions, unseen obstacles, vehicles with conflicting paths, and inattentive pedestrians. Interestingly, the same error-prone humans who are responsible for 94% of all accidents are able to seamlessly drive on unknown roads and to respond to unexpected behaviors by other vehicles on the road with minimal training (∼20 hours) compared to their AV counterparts that have been ‘trained’ on countless hours of simulation and road tests. The central approach currently followed by AV companies is to break the complex driving task into sub-tasks of sensing, perception, behavior prediction, planning and control. The presumption is that as these sub-tasks are solved with greater precision, we get closer to eliminating all traffic crashes.

The 94% statistic frequently quoted by AV companies has its origins in a report on national crashes published by the National Highway Transportation Safety Authority (NHTSA) in 2008 [1]. However, the actual statement in the report is as follows: It turns out that the 94% of crashes attributed to human error involve not just impaired or distracted driving, but also such causes as “false assumption of other’s actions”, “decision error”, “recognition error” and “inadequate surveillance”. This implies that all such crashes may not simply be a consequence of having reckless, error-prone humans at the wheel. Instead, many such crashes could be a result of unavoidable hazardous traffic scenarios the involved vehicles found themselves in. Even if AVs replace humans, it is unclear whether they will be able to avoid such crashes. What fraction of these crashes will be eliminated with the introduction of AVs on the roads remains an open question. The AV literature does not address this question.

An alternative technology could provide some clues to answer this question. The last couple of decades have seen rapid adoption of Advanced Driver Assistance Systems (ADAS). These include Automatic Emergency Braking (AEB), Lane Keeping Assist (LKA), and Adaptive Cruise Control (ACC). Like AV technology, these systems aim to eliminate human error by either assisting or warning the driver (eg., Forward Collision Warning) or automate driving in a well specified setting (eg., Automatic Parking). Each ADAS caters to a certain type of crash. For example, AEB and LKA reduce rear end and lane departure crashes respectively. It can be argued that for such types of crash scenarios, an AV can do no better than the corresponding ADAS. Thus, ADAS crash reduction studies could provide a good estimate for potential crash reduction due to AV technology. One such study analyzed the field effectiveness of General Motors ADAS based on safety data from 3,785,419 vehicles across 22 models [15]. It found that percent crash reduction ranged from 3% to 81% depending on the ADAS considered. Notably, while ADAS help improve traffic safety, they fail to prevent a significant proportion of system-relevant crashes. This might presage a similar outcome in the future with AVs. Another study predicting AV-related road traffic fatalities using the German In-Depth Accident Study database arrived at the same conclusion [16].
The NHTSA report on crashes in the period 2011-15 classifies crashes into 36 scenario types based on the events leading up to the crash [29]. For example, the crash type “Backing into Vehicle” includes all crashes in which a vehicle collides with another vehicle while backing. The report also contains the statistical distribution of crashes across these types. This can serve as a useful tool in understanding why crashes occur and what kind of crashes can be avoided by AVs. For instance, “Crossing Paths” is a grouping of 6 crash types involving two vehicles moving perpendicular to each other with conflicting paths – a common occurrence at intersections. This group accounts for 19% of all crashes and damages of $135.4 billion each year. An interesting aspect of such crashes is that it is often unclear which vehicle is at fault. There could be static obstacles or surrounding vehicles occluding the field of view of both parties involved so that they do not see each other until it is too late. Crossing Paths crashes could also occur due to one or more vehicles violating traffic rules such that their paths coincide. Even if AVs have perfect sensing and perception capabilities, they will not be immune to occlusions and as a result, will end up in such hazardous scenarios. “Changing Lanes” is another crash grouping that accounts for 12% of all crashes and damages of $32.9 billion every year. Lane changing involves searching for large enough gaps in traffic so as to safely complete the maneuver. Such large gaps may not always be available, especially during peak hours. In such circumstances with small traffic gaps, the lag vehicle either cooperates or is forced to create the required gap so that the ego vehicle can successfully change lanes. Thus, inaccurate predictions of the lag vehicle behavior can lead to dangerous scenarios which ultimately lead to crashes.

A common theme that ties together the crash scenarios discussed above is that connectivity with either infrastructure (I2V) or neighboring vehicles (V2V) would eliminate such crashes. In the case of occlusions and traffic violators at intersections, I2V communication would ensure that the involved vehicles “see” each other in time [9, 21, 25]. For the lane changing case, V2V communication would ensure that the involved parties are in agreement, thus preventing a potential hazardous situation [17, 32].

At the same time, relying on connectivity has its own costs. Foregoing connectivity allows companies to deploy their vehicles on the roads without having to wait for the required sensors and communication channels being set up. Moreover, security concerns arise with dependency on surrounding vehicles or infrastructure for information [4, 20]. Thus, an interesting question that arises in this context is whether it is possible to avoid crashes in the scenarios described above without relying on connectivity. In this paper, we argue that even with perfect sensing and perception capabilities, fully autonomous vehicles cannot guarantee safety in such scenarios. We develop a theoretical model for each of these scenarios in order to illustrate why such crashes will persist. We also discuss how connectivity with either infrastructure or surrounding vehicles can alleviate these safety concerns.

2 Occlusions

Let us consider a commonly occurring on-road occlusion scenario and analyze how an AV should act in order to be safe. Consider an AV at a signalized traffic intersection on the left-turning lane as illustrated in Figure 1. There is no protected left-turn phase, so it is waiting for gaps in traffic to make a left turn. The left-turn opposing lane is queued up, thus, blocking the AV’s view of through moving vehicles (TMVs) in the opposing lane. The objective of the AV is to choose the right time
Figure 1: AV (in yellow) making unprotected left turn with through moving vehicles occluded by queued up left-turning vehicles. The AV’s occluded field of view is illustrated by the shaded yellow region. The red box CZ denotes the conflict zone.

to make a left-turn so that it does not collide with through-moving traffic. This scenario falls within Crash Type 30: Left Turn Across Path/Other Direction (LTAP/OD) of the NHTSA crash typology which accounts for 5.8% of all crashes. Furthermore, such crossing path crashes have the highest comprehensive costs and equivalent lives lost among all crash groups in the NHTSA report [29]. Recognizing the safety costs of such crashes, fleet operators such as UPS design their routes so that they do not involve left turns [11].

We assume that the opposing through lane is free-flowing and the arrival of TMVs is modeled as a Poisson process with rate $\lambda$. We assume that the through moving vehicles are self-preserving but not anticipative, i.e., a through moving vehicle will make an evasive maneuver (for eg., hit the brakes) once it sees the left-turning AV, else it maintains its current speed. As AVs will have to drive among human drivers when they are introduced on the roads, we assume that all other vehicles are human driven with a reaction time $\rho \in [0.7, 2.5]$ \textsuperscript{1}. We maintain this assumption for the rest of the paper. We use the following values for relevant intersection geometry and vehicle parameters:

- Lane width - 4 m,
- Vehicle length - 4 m,
- Vehicle width - 2 m,
- Maximum acceleration rate - 3 m/s$^2$,
- Maximum deceleration rate - 4 m/s$^2$.

\textsuperscript{1}We use the term reaction time to refer to the total time required for perception (mental processing time for recognizing need for evasive action), driver response (time taken to make the evasive maneuver, for eg., hitting the brakes), and device response (time between driver’s action and corresponding vehicle response). This is also referred to as stopping time in the literature [8].
2.1 Can the AV make an unprotected left-turn with guaranteed safety?

We first aim to understand under what conditions an AV can make an unprotected left-turn irrespective of the arrival process of TMVs. In this case, the AV’s safety depends on whether the TMV can brake in time to avoid the AV. The worst possible case for an AV in such a situation is when the TMV is just beyond its field of view when it decides to make a left-turn. We use the term conflict zone to refer to the region of the intersection where the paths of the left-turning and through moving vehicles coincide - marked in red in Figure 1. Let $v_{th}$ and $a_{dec}$ denote the velocity and maximum deceleration rate of the TMVs. Let $d_{CZ}$ denote the distance from conflict zone at which the TMV first sees the AV. Based on the above parameters for intersection geometry and vehicle dimensions, $d_{CZ}$ turns out to be 12 m. As the TMV takes time $\rho$ to react to the left-turning AV, its distance from the conflict zone when it starts decelerating is $d_{CZ} - v_{th}\rho$. Assuming the TMV brakes at the maximum rate $a_{dec}$, it can avoid a crash with the AV as long as

$$v_{th}^2 \leq 2a_{dec}(d_{CZ} - v_{th}\rho). \quad (1)$$

Even under the most optimistic choice for TMV reaction time $\rho = 0.7$ s \cite{8}, an AV can be guaranteed to be safe only if the TMVs are moving at no more than 17 mph. This is much lower than typical through moving vehicle speeds observed at intersections, especially because they have right-of-way in such a setting. This suggests that an AV cannot guarantee safety while making an unprotected left-turn under such occlusions.

2.2 Can the AV be “safe enough” while making an unprotected left-turn?

Realizing that it is impossible to guarantee safety in this setting, let us consider an AV that is willing to accept a probability of collision no greater than $p_{coll}$ under such an occlusion. Note that the arrival rate $\lambda$ of TMVs is unknown to the AV apriori. Let us assume a through movement velocity $v_{th} = 25$ mph. We define exposure distance $d_{exp}$ as the TMV’s distance from the conflict zone at which it first sees the AV. Let $d_{min_{exp}}$ denote the minimum exposure distance such that the TMV can brake to a stop before reaching the conflict zone. If $d_{exp} < d_{min_{exp}}$, then we have a potential collision. Although we account for the TMVs attempting to brake when they see the AV, we do not consider more complicated evasive maneuvers like swerving that could also be used by the TMVs. Such scenarios in which a collision would occur unless evasive maneuvers are carried out by the involved vehicles are referred to as traffic conflicts\footnote{The traffic conflicts technique was introduced by Perkins and Harris as a surrogate measure of traffic safety \cite{23}. A traffic conflict is defined as an event that would lead to a crash unless an evasive action such as braking or swerving is taken. As traffic crashes are very rare events, actual crash data is scarce and unreliable as a safety metric. On the other hand, traffic conflicts are abundant and are amenable to empirical estimation. The estimated number of traffic conflicts can then be multiplied by a suitable factor depending on the traffic scenario to get the predicted number of traffic crashes.}. It is reasonable to expect that at least some of these traffic conflicts will result in crashes. We allow for the possibility of other evasive maneuvers being used by the TMVs by introducing $\gamma$ - the ratio of traffic conflicts to collisions. We analyze the probability of a traffic conflict and then translate it to a collision probability using the following equation:

$$P_{conf} = \gamma P_{coll}. \quad (2)$$

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Note that the conflict-to-collision ratio $\gamma$ depends on the scenario considered. For our analysis, we use $\gamma = 1490$ based on an empirical estimate of opposing left-turn conflict-to-collision ratio in \[7\].

Given that the TMV arrivals are Poisson, the probability of traffic conflict can be translated into the probability that there is a Poisson arrival in an interval of $t_{conf}$ sec, where

$$t_{conf} = \frac{d_{\text{min}} - d_{CZ}}{v_{th}}.$$  \hspace{1cm} (3)

If the AV were to know $\lambda$, its decision is straightforward. It should make the left-turn if the probability of at least one TMV arrival in a time interval of length $t_{conf}$ sec is less than the AV’s maximum allowed probability of traffic conflict, i.e.,

$$1 - e^{-\lambda t_{conf}} \leq p_{conf}.$$  \hspace{1cm} (4)

Thus, the AV would make the turn if $\lambda \leq \lambda_{\text{max}}$, where

$$\lambda_{\text{max}} = \frac{1}{t_{conf}} \log \left( \frac{1}{1 - p_{conf}} \right).$$  \hspace{1cm} (5)

However, the AV does not know $\lambda$. An interesting question arises in such a scenario: *In the time the AV waits at the intersection, can it estimate $\lambda$ with reasonable confidence such that it can make the left-turn when the situation is indeed safe?*

This question can be posed as a hypothesis testing problem:

$$H_0 : \lambda \geq \lambda_{\text{max}}, \quad H_1 : \lambda < \lambda_{\text{max}}.$$  \hspace{1cm} (6)

The AV observes through moving traffic while it waits for $t_{obs}$ seconds at the intersection. It decides to make the left turn if it can reject the null. For a level-$\alpha$ test, this implies that the AV makes the turn if it sees no TMV arrivals in $t_{obs}$ seconds, i.e.,

$$e^{-\lambda_{\text{max}} t_{obs}} \leq \alpha.$$  \hspace{1cm} (7)

Thus, we have

$$t_{obs} = \frac{1}{\lambda_{\text{max}}} \log \left( \frac{1}{\alpha} \right).$$  \hspace{1cm} (8)

It is not clear apriori what an acceptable collision probability $p_{\text{coll}}$ should be. We derive an upper bound $\bar{p}_{\text{coll}}$ for this quantity by choosing the intersection with the highest rate of opposing left-turn crashes in San Francisco as our baseline - Market Street and Octavia Street with 10 crashes in the period 2011-17 \[26\]. Then,

$$\bar{p}_{\text{coll}} = \frac{\text{Number of opposing left-turn crashes per year}}{\text{Number of left-turns under occlusion per year}}.$$  \hspace{1cm} (9)

\[3\]Table 8 in \[7\] contains conflict-to-collision ratios for traffic scenarios such as opposing left-turn, left-turn same direction and through cross traffic under varying traffic volumes. Note that the conflict-to-collision ratio $\gamma$ is the inverse of the accident/conflict ratio in Table 8.
Assuming that the occlusion scenario occurs during peak hours, we have

\[
\text{Number of left-turns under occlusion per year} = \text{Left-turn rate} \times \text{Number of peak hours per day} \times \text{Number of weekdays in a year.}
\]

Assuming a flow of 1000 vehicles/hr through the intersection and 10% of vehicles turning left on average, we have a left-turn rate of 100 turns/hr. Assuming 4 peak hours/weekday, we get \( \bar{p}_{\text{coll}} = 1.4 \times 10^{-5} \). We use this upper bound in our calculations to get a lower bound for \( t_{\text{obs}} \) using (8). We use \( \gamma = 1490 \) based on [7]. As \( p_{\text{conf}} = \gamma \bar{p}_{\text{coll}} = 2.1 \times 10^{-2} \), we choose \( \alpha = 10^{-4} \) for the hypothesis testing problem. As \( v_{\text{th}} = 25 \text{ mph} (11.18 \text{ m/s}) \), we get \( d_{\text{exp}}^\text{min} = 23.45 \text{ m} \) using (1). Plugging in our model parameters, it turns out that the AV needs to observe traffic for \( t_{\text{obs}} = 443 \) seconds in order to make its decision to turn. Clearly, this is prohibitively high and hence, the AV cannot safely make the turn with the required collision probability.4

2.3 Occluded Pedestrians

The scenario considered in the previous subsections gets even more challenging when there are pedestrians involved. Crashes involving pedestrians have the highest fatality rate among all crash groupings in the NHTSA typology [29]. Such crashes account for 58% of all fatal crashes near intersections in the city of San Francisco [26]. In what follows, we investigate the role of occlusions in causing such crashes.

The NHTSA pre-crash scenario typology includes two crash types to classify vehicle-pedestrian crashes based on whether the vehicle is performing a maneuver (e.g., passing, turning) - Crash Type 10: Pedestrian/Maneuver and Crash Type 11: Pedestrian/No Maneuver [29]. However, it does not specify if occlusions contributed to the crash. Through a further classification of the above crash types based on possible occlusions, we arrive at three pre-crash scenarios in which pedestrians being occluded by a surrounding vehicle leads to a crash as illustrated in Figure 2.

- **Pedestrian/Maneuver Type 1**: The AV is turning left at the beginning of its green phase while pedestrians are trying to cross as soon as possible since the pedestrian phase is changing from the flashing phase to red. The field of view of the left-turning AV is occluded by queued up vehicles on the adjacent right lane. Such a scenario can occur in both protected and permissive left turn signal phases.

- **Pedestrian/Maneuver Type 2**: As the left-turning AV enters the intersection, it cannot detect pedestrians on the crosswalk as its field of view is obstructed by the through moving vehicles. This results in a crash if the AV cannot brake in time to avoid the pedestrians. Such a situation can arise during the permissive left-turn phase.

- **Pedestrian/No Maneuver**: The field of view of the through moving AV is occluded by stopped vehicles on adjacent lanes. At the beginning of the green through phase, the AV might collide with pedestrians who could not finish crossing during the previous phase, especially those who entered the crosswalk during the yellow phase.

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4As we already account for braking action by TMVs, the conflict-to-collision ratio \( \gamma \) chosen for our analysis is considerably larger than the actual \( \gamma \) for the given setting. Thus, the required waiting time at the intersection is even larger than what we have calculated.
Figure 2: Three pre-crash scenarios with occluded pedestrians: AV (in yellow) is occluded by stopped or moving vehicles (in blue), and the AV’s occluded field of view is illustrated by the shaded yellow region.

We model pedestrians as Poisson arrivals on the crosswalk moving at a fixed velocity. We assume that they are inattentive and as a result, do not attempt to evade the AV. Although this is not always the case, such inattentive behavior is commonly observed during changes in signal phase when pedestrians hastily attempt to cross to the other side of the road. We use the term *pedestrian conflict zone* to refer to the region of crosswalk coinciding with the AV’s path. For our analysis, $t = 0$ is the time at which the AV first detects the pedestrian. We introduce the following notation:

- $\lambda_{\text{ped}}$: arrival rate (ped/s) of pedestrians,
- $v_{\text{ped}}$: pedestrian speed (m/s) when crossing on yellow/flashing phase/at the end of pedestrian phase,
- $D_{\text{ped to crash}}$: distance (m) from pedestrian’s position at $t = 0$ to the center of pedestrian conflict zone,
- $v_{\text{veh left}}$: the left-turn speed (m/s),
- $v_{\text{th}}$: the through speed (m/s) before/at the intersection,
- $D_{\text{veh to crash}}$: distance (m) from vehicle’s position at $t = 0$ to the pedestrian conflict zone,
- $a_{\text{acc}}$: maximum AV acceleration rate (m/s$^2$),
- $a_{\text{dec}}$: maximum AV deceleration rate (m/s$^2$),
- $w_{\text{AV}}$: Width of AV (m).

We begin our analysis with the *Pedestrian/Maneuver Type 2* scenario, and then show how this approach can be suitably modified to accommodate the other two scenarios. Notice that the following conditions need to satisfied for a *Pedestrian/Maneuver Type 2* scenario to end up in a crash:
• **Condition 1:** The AV’s view of the crosswalk is obstructed by passing through moving vehicles when it is making an unprotected left-turn.

• **Condition 2:** When the AV finally detects the pedestrian, it does not have enough time to brake to a stop before the conflict zone.

Assuming that both the above conditions hold, a crash can occur if the pedestrian’s original trajectory coincides with that of the AV. When the AV first detects the pedestrian, it has two choices depending on the location of the pedestrian on the crosswalk: decelerate so that pedestrian can cross the conflict zone before it reaches there or accelerate and cross the conflict zone before the pedestrian arrives there. As we do not account for pedestrians being attentive or more complicated maneuvers such as swerving by the AV, we classify such a scenario as a traffic conflict, as in Section 2.2. Let $\delta$ denote the time required by pedestrian to cross the conflict zone, i.e., $\delta = \frac{w_{AV}}{v_{ped}}$. Let $t_{acc}$ denote the time taken by the AV to reach the conflict zone while it accelerates. Then,

$$t_{acc} = \frac{\sqrt{2a_{acc}D_{veh, to, crash} + v_{veh, left}^2 - v_{veh, left}^2}}{a_{acc}}. \quad (11)$$

In this case, a conflict occurs if the pedestrian arrives at the center of the conflict zone in the time interval $T_{acc} = [t_{acc} - \delta/2, t_{acc} + \delta/2]$. Let $t_{dec}$ denote the time taken by AV to reach the conflict zone while it decelerates. Then, we have

$$t_{dec} = \frac{v_{veh, left} - \sqrt{v_{veh, left}^2 - 2a_{dec}D_{veh, to, crash}}}{a_{dec}}. \quad (12)$$

In this case, a conflict occurs if the pedestrian arrives at the center of the pedestrian conflict zone in the time interval $T_{dec} = [t_{dec} - \delta/2, t_{dec} + \delta/2]$. Thus, a conflict is unavoidable if the pedestrian arrives in the time interval $T_{acc} \cap T_{dec} = [t_{dec} - \delta/2, t_{acc} + \delta/2]$. This translates into the following condition on $D_{ped, to, crash}$:

$$D_{ped, to, crash} \in [\max(0, (t_{dec} - \delta/2)v_{ped}), (t_{acc} + \delta/2)v_{ped}]. \quad (13)$$
The probability of this event can be interpreted as the probability of arrival of at least one pedestrian in a time interval of length \((t_{acc} - t_{dec} + \delta)\). As the pedestrian arrival process is Poisson with rate \(\lambda_{ped}\), we have

\[
P_{\text{scenario2}}(\text{Conflict — Conditions 1 and 2 hold}) = 1 - e^{-\lambda_{ped}(t_{acc} - t_{dec} + \delta)}. \tag{14}
\]

Based on intersection geometry and commonly observed values for the model parameters, we have:

- \(v_{ped} = 2 \text{ m/s}, \quad \lambda_{ped} = \frac{1}{60} \text{ ped/s}, \quad w_{AV} = 2 \text{ m}, \quad v_{veh,left} = 15 \text{ mph (6.71 m/s)}, \quad D_{veh,to\text{-crash}} = 4 \text{ m}, \quad a_{acc} = 3 \text{ m/s}^2, \quad \text{and } a_{dec} = 4 \text{ m/s}^2.\)

Then, \(\delta = w_{AV}/v_{ped} = 1 \text{ sec.}\) Using (11), (12), (13), and (14), we have

\[
D_{\text{ped,to\text{-crash}}} \in [0.55, 2.07] \text{ m},
\]

\[
P_{\text{scenario2}}(\text{Conflict — Conditions 1 and 2 hold}) = 0.0125. \tag{15}
\]

The above analysis can be conveniently modified for the other two scenarios. For the Pedestrian/No Maneuver scenario, Condition 1 should be rephrased as: “The AV’s view of the crosswalk is occluded by stopped vehicles in the adjacent lane when it is passing through the intersection at the beginning of the green phase”. Condition 2 remains the same. The probability computation in (11) and (12) are hence modified as follows while (14) remains the same:

\[
t_{acc} = \frac{\sqrt{2a_{acc}D_{veh,to\text{-crash}}} + v_{th}^2}{a_{acc}}, \tag{16}
\]

\[
t_{dec} = \frac{v_{th} - \sqrt{v_{th}^2 - 2a_{dec}D_{veh,to\text{-crash}}}}{a_{dec}}. \tag{17}
\]

In this scenario, we have \(v_{th} = 25 \text{ mph (11.18 m/s)}\) and \(D_{veh,to\text{-crash}} = 4 \text{ m}.\) The rest of the parameters remain the same as above. Using (13), (14), (16), and (17), we have

\[
D_{\text{ped,to\text{-crash}}} \in [0, 1.68] \text{ m},
\]

\[
P_{\text{scenario3}}(\text{Conflict — Conditions 1 and 2 hold}) = 0.0158. \tag{18}
\]

Similarly, for Pedestrian/Maneuver Type 1, we set \(v_{veh,left} = 4.5 \text{ m/s}\) and \(D_{veh,to\text{-crash}} = 3 \text{ m}\) while keeping the the rest of the parameters same as in Pedestrian/Maneuver Type 2. Then, we have

\[
D_{\text{ped,to\text{-crash}}} \in [0.063, 1.82] \text{ m},
\]

\[
P_{\text{scenario1}}(\text{Conflict — Conditions 1 and 2 hold}) = 0.0145. \tag{19}
\]

So far, we have calculated conflict probabilities for the three scenarios which are in the range [0.0125, 0.0158]. As in (2), this conflict probability can be translated into a collision probability as follows:

\[
P(\text{Collision — Conditions 1 and 2 hold}) = \frac{P(\text{Conflict — Conditions 1 and 2 hold})}{\gamma},
\]

where \(\gamma\) is the conflict-to-collision ratio for the corresponding pedestrian occlusion scenario. Although we are not aware of any empirical estimates for \(\gamma\) specific to scenarios involving pedestrians, it is reasonable to expect that \(\gamma\) should be lower than that for the various scenarios considered in [7]. There are two reasons for this: (i) the empirical estimates are not conditioned on occlusions,
and (ii) we account for basic evasive maneuvers such as braking by the AV. Even if we set $\gamma$ as the largest observed value across all scenarios in [7], we have

$$P(\text{Collision — Conditions 1 and 2 hold}) \approx 2.8 \times 10^{-6},$$

(20)

which is significantly high considering that such occlusions are commonplace in urban driving situations. Due to the reasons mentioned above, we can expect this collision probability to be considerably higher. This strongly suggests that such occlusions are a major cause of crashes involving pedestrians.

2.4 How can such crashes be prevented?

It is clear that under the occlusion scenarios described above, an AV cannot guarantee safety despite having perfect sensing and perception capabilities. The underlying cause of such crashes is the inability to detect vehicles or pedestrians on conflicting paths in time to take evasive action. Thus, mitigating such crashes requires additional communication between vehicles and the infrastructure so that this critical information is relayed to the necessary parties in time. The vehicle-vehicle scenario illustrated in Figure 1 can be prevented by placing a sensor on the through moving lane at a sufficient distance from the conflict zone depending on the through moving vehicle speeds. For example, if the speed limit on the through moving lane is 30 mph and considering a worst case human reaction time $\rho = 2.5$ s, a sensor placed at 56 m from the conflict zone will provide enough time for the TMV to prevent the impending crash [21]. In the vehicle-pedestrian scenario illustrated in Figure 3, an additional sensor detecting pedestrian movement on the crosswalk would be required to prevent the crash.

3 Traffic Violation

Traffic violation is one of the leading causes of crashes on the roads, accounting for 32% of all crashes [29]. Red light running is a common violation that is responsible for a large number of crashes each year. Figure 4 depicts the setup for a conflict resulting from this violation. Vehicle V (violator) is going with speed $v_V$ from south to north and runs the red light. Vehicle E (ego vehicle) has the right of way traveling from west to east. In the following analysis, we compute the probability of a conflict between vehicles E and V. Recall that a conflict does not mean crash, but rather a hazardous situation that may lead to a crash, as discussed in Section 2. We consider the violation scenario from the point of view of an ego-vehicle. Therefore, we compute the conflict probability under the condition that vehicle E is present at the intersection.

As discussed in [22], at intersections equipped with stop bar detectors and a conflict monitoring card that provides programmatic access to a signal phase, it is possible to monitor red light violations and collect corresponding statistics. An example of such data, collected at the intersection of Montrose Parkway and E. Jefferson Street in North Bethesda, MD, is presented in Figure 5.\footnote{Note the spike of violations in the east and less in the west directions between midnight and 6 A.M. This could be explained by the fact that the southbound direction leads to the Kaiser hospital, and during the night the south-to-north approach has practically no traffic. Hence, eastbound and westbound violators feel relatively safe, not expecting danger from that approach during night hours. Shortly before 6 A.M. the situation changes sharply, as traffic to the hospital starts to increase.}
Figure 4: Two scenarios of red light violations: (a) vehicles with a right of way wait in queue and slowly start moving as the light changes to green; (b) vehicles with a right of way randomly arrive during green time.

\[ \nu_A(t) \] denote the expected number of violations for a given approach A and a given time \( t \). On the south-to-north (northbound – NB) approach, we have \( \nu_{NB} = 0.67 \) violations between 4:00 and 4:15 A.M., and \( \nu_{NB} = 1.91 \) violations between 12:00 and 12:15 P.M.. These values for the given time intervals are averaged over a period of one year, from 02/01/2019 through 01/31/2020.

Figure 5: Intersection of Montrose Parkway and E. Jefferson Street in North Bethesda, MD: Statistics of red light violations collected over one year from 02/01/2019 through 01/31/2020.

We assume that a red light violation occurs shortly after the signal phase change: when the green (or yellow) light for vehicle V switches to red.\(^6\) Suppose, an average signal cycle length is \( T_c \), so over a period \( \Delta T \) we expect to have \( \Delta T/T_c \) green-to-red switches. Then, the probability of a violation

\[ ^6 \text{Violating late in the red phase would imply a malicious intent, a rather rare occasion, which we do not consider.} \]
from approach A during a green-to-red switch is

\[ p^V_A(t) = \frac{T_c \nu_A(t)}{\Delta T}. \tag{21} \]

Thus, given the cycle length \( T_c = 150 \) seconds at our intersection of Montrose Parkway / E. Jefferson Street and \( \Delta T = 900 \) seconds, we get \( p^V_{NB} = 0.67/6 = 0.11 \) between 4:00 and 4:15 A.M. and \( p^V_{NB} = 1.91/6 = 0.32 \) between 12:00 and 12:15 P.M.

Let us now discuss the probability of a conflict between vehicles E and V. Such a conflict, if it occurs, happens in the conflict zone CZ, indicated by a dashed line in Figure 4. Let \( d_y \) denote the south-to-north size of this conflict zone – i.e., the distance vehicle V has to cover being exposed to a conflict with vehicle E. This distance includes the expected length of vehicle V itself. In our sample intersection, \( d_y = 17 \) meters (the expected length of vehicle V is 5 meters). The time taken by vehicle V to cross the conflict zone is

\[ t_{\text{cross}} = t_d + d_y/v_V. \tag{22} \]

Here, \( t_d \) is the time interval between the signal phase switch and the instant when vehicle V reaches the conflict zone CZ. The arrival of vehicle E at the intersection during the violator’s crossing can happen in two ways:

(a) Vehicle E drives through the intersection at the moment of the signal phase switch and, as the its light turns from red to green, at a constant speed without stopping. This case is depicted in Figure 4(a).

(b) Vehicle E is already there – waiting at the red light. And, as soon as the light turns green, it starts moving. This case is depicted in Figure 4(b).

Since we compute the conflict probability under the assumption that the ego-vehicle is present in the intersection, for both cases (a) and (b), \( p^E_{EB} = 1 \).

It remains to compute the probability of a conflict between vehicles V and E under the condition that vehicle V runs the red light and vehicle E is also present at the intersection. Let \( d_{\text{CZ}} \) denote the distance from the stop bar of the west-to-east approach to the conflict zone CZ, and \( d_x \) – the size of the conflict zone CZ in the west-to-east direction. Distance \( d_x \) includes an expected length of vehicle E. In our sample intersection, \( d_{\text{CZ}} = 16 \) meters and \( d_x = 16 \) meters (accounts for 5 meters of the expected length of vehicle E).

A conflict exists when both vehicles, V and E, are present in the conflict zone CZ simultaneously. This happens if the following condition holds:

- Case (a):

\[ \frac{d_{\text{CZ}}}{t_d + d_y/v_V} < v_E \leq \frac{d_{\text{CZ}} + d_x}{t_d}. \tag{23} \]

where \( v_E \) is the speed with which vehicle E arrives at and goes through the intersection.
• Case (b):

\[ \frac{2d_{CZ}}{(td + dy/v_V)^2} < a_E \leq \frac{2d_{CZ} + dx}{t_d^2}, \]  

(24)

where \( a_E \) is the acceleration with which vehicle E starts moving once its light turns green.

It is possible to estimate the probabilities of conditions (23) and (24) for different delay periods \( t_d \), if we have some idea about the range of values for \( v_V, v_E \) and \( a_E \).

At the intersection of Montrose Parkway and E. Jefferson Street the speed limit in direction south-to-north is 25 mph (11.18 m/s). To be more conservative, we will assume the speed of the violator, \( v_V = 10 \) m/s. The speed of vehicles crossing this intersection in the west-to-east direction measured by the detectors is presented in the histogram in Figure 6. The typical vehicle acceleration from the intersection stop bar after its light turns green ranges between 1 and 2 m/s\(^2\). Assuming that \( a_E \sim \mathcal{N}(1.5, 0.25) \), we can estimate the conditional probabilities of the conflict between vehicles E and V for cases (a) and (b) for different values of \( t_d \) – see Figure 7.

![Figure 6: Distribution of speeds \( v_E \), with which vehicles cross the intersection of Montrose Parkway and E. Jefferson Street in the west-to-east direction. The speed values are taken over a random week of 2019.](image)

Finally, we can express the probability of a conflict between vehicles E and V:

\[
p_{\text{conflict}} = \begin{cases} 
  p_{NB}^V \left( \frac{d_{CZ}}{td + dy/v_V} < v_E \leq \frac{d_{CZ} + dx}{t_d} \right), & \text{case (a)}, \\
  p_{NB}^V \left( 2 \frac{d_{CZ}}{(td + dy/v_V)^2} < a_E \leq \frac{2d_{CZ} + dx}{t_d^2} \right), & \text{case (b)}, 
\end{cases} \]

(25)

where \( p_{NB}^V \) and is determined from (21).

Given the parameters of our intersection, these probabilities are presented in Figure 8 for two time periods: 4:00-4:15 A.M. and 12:00-12:15 P.M..

These conflict probabilities can be translated into collision probabilities using (2) with \( \gamma = 2040 \) estimated for the through-cross traffic scenario in [7]. Based on a similar argument as in Section 2.
Figure 7: Probabilities of a conflict under the condition that both vehicles, V and E, arrive at the intersection of Montrose Parkway and E. Jefferson Street at the same time – cases (a) and (b).

Figure 8: Conflict probability computed using data from intersection of Montrose Parkway and E. Jefferson Street for cases (a) and (b).

this suggests that such crashes will occur with a considerably high probability, which might explain why traffic violations are involved in one-third of all crashes. If we think of the ego-vehicle as an AV attempting to pass the intersection, it is evident that such traffic violations will jeopardize its safety.

The probability of such a conflict could be reduced by I2V technology, provided that vehicle E and the roadside infrastructure were connected. The violator V would be detected by combining stop bar sensor activation with a signal phasing. Then a notification about a violation in a certain direction would be broadcast by the roadside equipment. Intersection conflict avoidance (ICA) defined in the SAE J2735 standard could be used for this purpose. If vehicle E receives this broadcast before it reaches the conflict zone CZ, it should brake. If, on the other hand, it is already inside CZ, it should accelerate to clear the conflict zone faster.
4 Behavior Prediction Uncertainty

One of the most challenging aspects of driving on the roads is that one’s own safety depends on the behavior of surrounding vehicles. As humans, predicting the actions of vehicles around us is a key component of the driving process. Attempts are being made to imbue AVs with the same capability by training systems with large amounts of driving data. As there is a vast multitude of driving scenarios and driver behaviors, it is unclear how well such systems generalize to unseen situations. What makes such a prediction task even more challenging is that one’s own actions affect surrounding vehicle behavior \cite{24,27}. For AVs that depend on such behavior prediction modules for planning, inaccuracies in prediction can result in hazardous scenarios. An alternate approach that circumvents the challenge of behavior prediction is to plan based on the worst-case behavior of surrounding vehicles \cite{28}. Although this seems appealing from a safety perspective, it is unclear whether such an approach is feasible in the real world. If not, uncertainty in behavior prediction will indeed result in crashes. In this section, we investigate whether this is the case using empirical data for a common on-road scenario - merging on to a freeway.

Consider an AV attempting to merge from an on-ramp on to a freeway. As in Section 2, all other vehicles are human driven. The AV decides to merge if the gap between the lead and lag vehicle on the merging lane is large enough. This scenario falls within Type 16 - Changing Lanes/Same Direction in the NHTSA pre-crash scenario typology which accounts for 6.2% of all crashes. Moreover, this scenario is particularly relevant for AVs as there have been several accounts of them having difficulties merging into traffic \cite{19}.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{fig9.png}
\caption{An AV (in yellow) merging from on-ramp on to freeway.}
\end{figure}

We assume that vehicles on the freeway respond to changes in velocity of vehicles in front of them and take evasive action to avoid a crash, albeit with a reaction time. Let $\rho_{AV}$ and $\rho_B$ denote the reaction times of the AV and lag vehicle respectively. Let $v_{AV}$, $v_F$, and $v_B$ denote the speeds of the AV, lead and lag vehicles at the time of the AV’s merging decision. Let $d_F$ and $d_B$ denote the gaps between the lead vehicle and AV, and lag vehicle and AV respectively. We assume that all vehicles have the same maximum acceleration and deceleration rates, $a_\text{acc}$ and $a_\text{dec}$ respectively. In order to guarantee safety, the AV must be able to safely evade any potential collision with the lead or lag vehicle regardless of their actions. This implies that the AV must be safe in each of the following worst-case scenarios:
Table 1: Observed and safe merging gaps for the NGSIM US-101 dataset.

| Time    | Observed Merging Gap (m) | Safe Merging Gap (m) |
|---------|--------------------------|----------------------|
| 7:50 - 8:05 | 43.19                    | 93.79                |
| 8:05 - 8:20 | 35.63                    | 84.22                |
| 8:20 - 8:35 | 27.44                    | 75.90                |

1. Lead vehicle decelerates to a stop while AV merges,
2. Lag vehicle accelerates while AV merges.

Then, the safe distance for merging $d_{\text{safe}}$ can be decomposed as follows:

$$d_{\text{safe}} = d_{F,\text{safe}} + d_{B,\text{safe}} + l_{AV},$$

where $d_{F,\text{safe}}$ and $d_{B,\text{safe}}$ denote the minimum distance required to avoid a collision in cases (i) and (ii) respectively, and $l_{AV}$ denotes the length of the AV. In case (i), the lead vehicle brakes to a stop and the AV is able to react only after $\rho_{AV}$ seconds, before which it maintains its initial velocity $v_{AV}$. Then, the AV can safely evade a collision if its distance from the lead vehicle $d_F$ satisfies

$$d_F + \frac{v_F^2}{2a_{\text{dec}}} \geq v_{AV}\rho_{AV} + \frac{v_{AV}^2}{2a_{\text{dec}}}.$$  

This gives us

$$d_{F,\text{safe}} = \max \left\{ v_{AV}\rho_{AV} + \frac{v_{AV}^2 - v_F^2}{2a_{\text{dec}}}, 0 \right\}.$$  

In case (ii), the lag vehicle accelerates for $\rho_{B}$ until it realizes that the AV is merging, after which it decelerates to avoid crashing into the AV. The worst case in such a setting is if the AV is forced to brake to a stop because of the lead vehicle decelerating to a stop. Thus, a collision with the lag vehicle can be avoided as long as the gap $d_B$ satisfies

$$d_B + \frac{v_{AV}^2}{2a_{\text{dec}}} \geq v_{B}\rho_{B} + \frac{1}{2}a_{\text{acc}}\rho_{B}^2 + \frac{(v_{B} + \rho_{B}a_{\text{acc}})^2}{2a_{\text{dec}}}.$$  

Thus, we have

$$d_{B,\text{safe}} = \max \left\{ v_{B}\rho_{B} + \frac{1}{2}a_{\text{acc}}\rho_{B}^2 + \frac{(v_{B} + \rho_{B}a_{\text{acc}})^2 - v_{AV}^2}{2a_{\text{dec}}}, 0 \right\}.$$  

We use the NGSIM US-101 dataset [2] to get estimates for vehicle velocities ($v_{AV}, v_F, v_B$) and observed merging gaps for three 15 minute intervals between 7:50 A.M. and 8:35 A.M. As the AV is accounting for the worst-case, we set the lag vehicle reaction time $\rho_{B} = 2.5$ sec according to the American Association of State Highway and Transportation Officials (AASHTO) design specifications based on the 95th percentile of empirical reaction time estimates - see Table 3 in [30]. We set $\rho_{AV} = 0.83$ sec, which is the mean of empirically observed AV reaction times - see Table 2 in [6]. Using the following values for the rest of our problem parameters: $a_{\text{acc}} = 3$ m/s$^2$, $a_{\text{dec}} = 4$ m/s$^2$
and $l_{AV} = 4$ m, we compute the safe merging gap $d_{safe}$ for each of the time intervals as seen in Table 1. It can be observed that the observed merging gaps are considerably smaller than the corresponding safe merging gaps. Thus, the worst-case planning approach is not feasible in this scenario. Unless the AV predicts the behavior of vehicles in the merging lane accurately, it cannot merge with guaranteed safety. Thus, behavior prediction uncertainty will indeed result in crashes. Deriving estimates for crash probability in this setting is challenging as it requires a model for how vehicles react to surrounding vehicle behavior as well as a probability distribution over possible vehicle behaviors. However, the fact that behavior prediction modules are not always accurate combined with the large number of merging crashes observed each year strongly suggests that such crashes will persist with a significantly high probability.

The fundamental safety issue in the above merging example is that it requires all the involved vehicles to be in agreement to ensure safety. In the absence of connectivity, predicting vehicle behavior and planning accordingly is the only available recourse. Introducing connectivity between vehicles (V2V) would obviate the need for such behavior prediction and as a result, ensure that the merging maneuver can be executed safely [17, 32].

5 Conclusion

Autonomous vehicles (AVs) have the potential to change the transportation landscape as we know it and lead us to a safer future. It makes intuitive sense that the thousands of lives that are unfortunately lost every year due to impaired, inattentive or reckless driving could be saved if human drivers are replaced with AVs. However, a significant fraction of crashes cannot be explained by these reasons. Instead, they are a consequence of a fundamental aspect of driving on the roads: Our safety depends not only on our own actions but also the positions and actions of surrounding vehicles - both of which might be unknown/partially known to us. In the absence of connectivity with surrounding vehicles (V2V) or infrastructure (I2V), it is unclear whether AVs can avoid such crashes. Even so, AV companies maintain that they will eventually eliminate all crashes without relying on connectivity.

One proposed approach is to assume worst-case positions and actions of surrounding vehicles and plan accordingly to be safe [28]. While this seems appealing as it circumvents the challenges associated with behavior prediction and does not require connectivity, it turns out that such guaranteed safety comes at a massive cost to traffic efficiency. As we show in our analysis, ensuring guaranteed safety would preclude vehicles from performing basic maneuvers like merging or unprotected left-turns in common traffic scenarios. In the presence of uncertainty about surrounding vehicle positions and behavior, some crashes are indeed unavoidable.

In this paper, we investigate three crash causes that tease out various aspects that make driving on the roads challenging: (a) Occluded Vehicles/Pedestrians (unknown vehicle position), (b) Traffic Violations (rule-following assumption violated), and (c) Behavior Prediction Uncertainty (inability to accurately predict vehicle actions based on past observations). For each of these cases, we show that it is impossible to guarantee worst-case safety without connectivity. We also provide some estimates for the probability of a crash in such scenarios.

Recognizing that such situations are inevitable while driving on the roads, the objective of an AV should be to manage crash risk while maintaining efficiency. Assessing crash probabilities
in commonly occurring risky scenarios is an important step in this process. As we assume perfect sensing and perception capabilities for AVs and idealized scenarios for our analysis, our estimates can be considered as lower bounds for actual crash probabilities. More realistic bounds can be derived by considering imperfections in road-user behavior and AV capabilities, as well as factors such as vehicle failures, and varied road geometry and conditions. Looking through the lens of managing crash risk, AVs can be seen as a collection of Advanced Driver Assistance Systems (ADAS). Thus, empirical estimates of ADAS effectiveness can be used to arrive at better estimates of crash reduction due to AVs [15].

The crashes we have discussed above result from lack of observability of surrounding vehicle positions or incorrect assumptions or predictions about vehicle actions. Communication with surrounding vehicles or infrastructure would ensure that all involved vehicles can “see” each other and reach an agreement regarding each others’ proposed actions [17, 21, 25, 32]. Thus, connectivity can bring about a significant reduction in otherwise unavoidable crashes. However, connectivity comes with its own safety challenges. Relying on information from other vehicles or infrastructure makes one vulnerable to security attacks from malicious road users that can jeopardize safety. Additionally, installing sensors on the roads and ensuring that all vehicles have the required technology to communicate would require a significant amount of time and economic resources. In order to reap the safety benefits of connectivity, active research is needed to minimize its associated safety risks as well as economic costs. Our hope for a future with zero crashes depends on it.

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