CAN BIKE-TO-CAR COMMUNICATION PREVENT CYCLIST FATALITIES?

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ABSTRACT

The overall number of fatalities in traffic accidents in Europe is decreasing substantially. Unfortunately, the number of fatalities among cyclists does not follow this trend. From the accident statistics it becomes clear that a major share of these killed cyclists in traffic accidents results from a collision with a motorized vehicle. The automotive industry focusses on this issue in terms of passive and active safety. One of the most promising active safety systems is an autonomous emergency braking system (AEB). Both simulation and first implementation results showed that preventing all defined accident scenarios is not currently possible due to the limitations of the sensors and perception algorithms, which means that cyclists are still at risk.

A possible solution to increase this AEB performance of the car is to add communication from the cyclist to the car. For that purpose Bosch, Shimano and TNO have formed a consortium to initiate a simulation study which is able to model the relevant accident scenarios, in-vehicle sensors, AEB logic, vehicle dynamic and communication in a realistic manner. In this study the benefit of several forms of communication, each with its own advantages and drawbacks, are added to current and future in-vehicle sensors. Two types of messages will be send: kinematic information and the prediction of the cyclist. The communication is either used as a sensor or as preparation, where in the latter the kinematic information is not used in the AEB logic.

A benefit analysis showed that adding communication is most beneficial for in-vehicle systems with large classification- and internal delays. To achieve a high total benefit, a large field of view is also needed if the preparation strategy is used instead of the sensor strategy.

Keywords: AEB, Simulation, Communication, Benefit, Effectiveness, Prevention

INTRODUCTION

The overall number of fatalities in traffic accidents in Europe is decreasing substantially. Unfortunately, the number of fatalities among cyclists does not follow the same trend and cyclists fatalities become a larger share every year (CARE, 2020, Uittenbogaard et al, 2015a). In The Netherlands, where the percentage of cyclist fatalities is the largest in Europe, the number of killed cyclists even surpassed the number of killed car occupants in 2017 (CARE, 2020). The
European Commission also clearly recognizes this trend and concludes that cyclists deserve special attention from policymakers (European Commission, 2018).

From the accident statistics it becomes clear that a major share of these killed cyclists in traffic accidents results from a collision with a motorized vehicle (European Commission, 2014). The automotive industry focusses on this issue in terms of passive and active safety. One of the most promising active safety systems is an autonomous emergency braking system (AEB). Such systems are able to apply full or partial braking to avoid or mitigate imminent crashes. Since 2014, AEB systems that aim at avoiding and mitigating car-to-car rear end collisions are part of the Euro NCAP (New Car Assessment Program) star rating. In 2016 and 2018, Euro NCAP introduced AEB for pedestrians and cyclists as part of their test and assessment procedure, respectively (Euro NCAP, 2019) and will extend it in the coming years (Euro NCAP, 2018). Both the simulation and first implementation results from the Cyclist AEB Testing System (CATS) project showed that preventing all defined accident scenarios is not currently possible due to the limitations of the sensors and perception algorithms (Uittenbogaard, 2016), which means that cyclists are still at risk of getting killed or injured.

A possible solution to increase this AEB performance of the car is to add communication from the cyclist to the car. This study uses a simulation approach to investigate the potential benefit, in terms of lives saved and injuries prevented, of adding this communication compared to cyclist-AEB based on in-vehicle sensors only. This is done by simulating various car-to-cyclist impact scenarios with different in-vehicle sensors combined with multiple communication methods and communication strategies.

2 METHOD

2.1 Simulation tool

The simulation tool selected is originally made to assess the AEB test protocol developed in CATS before presenting it to Euro NCAP. The goal was to make an accurate assessment of the AEB test protocol developed in the CATS project in terms of performance and ability to discriminate high and lower performing systems (de Gelder and Fusco, 2015). It is based on Matlab/Simulink and it is a deterministic tool. Verification was performed in order to check if realistic results could be produced (Uittenbogaard et al, 2016). A major advantage of this tool is that many scenarios can be simulated as it takes seconds to perform a single simulation.

2.2 Scenario description

As the main source of information the scenario description from the CATS project is used (Uittenbogaard et al, 2015b; van Dam et al, 2016), which used its own accidentology data. The velocity ranges are updated in this study to cover a 90% range. The scenarios consist of a nearside crossing with the most average parameters and a far-side crossing with more challenging parameters (cyclist speed and hit point). Furthermore a scenario is present for the nearside crossing with a view blocking obstruction since this was present in 40-60% of all crossing accidents. In the longitudinal accident scenario, only the obstructed part in is selected, since communication is expected to have no benefit in the unobstructed part due to the cyclist always being in the path of the car and field of view of the in-vehicle sensor. Additionally this study looks into accident scenarios which do not necessary occur often, but induce the most fear in cyclists. The one additional accident scenario that showed this effect is the blind spot scenario where the car turns into the nearside cyclist (Forsa, 2017; SWOV, 2015).

The proposed test scenarios can be found in Table 1 including their respective relative estimated coverage they represent, which will be used in the benefit analysis.
The vehicle geometry is based on an average size vehicle with a length of 4.5m and a width of 1.9m with a rounded front bumper. The cyclist geometry is based on the cyclist dummy developed in the CATS project and currently used in Euro NCAP testing (Fritz, 2016).

### Table 1. Proposed test scenarios for evaluation. (K= killed, SI = seriously injured). Total coverage is 60% for killed cyclists and 59% for seriously injured cyclists.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>CVNBU</th>
<th>CVNBO</th>
<th>CVFB</th>
<th>CVLO</th>
<th>CVBB</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vehicle speed</td>
<td>5 - 80 km/h</td>
<td>5 - 50 km/h</td>
<td>5 - 60 km/h</td>
<td>20 - 80 km/h</td>
<td>5 - 30 km/h</td>
</tr>
<tr>
<td>Cyclist speed</td>
<td>15 km/h</td>
<td>10 km/h</td>
<td>20 km/h</td>
<td>15 km/h</td>
<td>10 km/h</td>
</tr>
<tr>
<td>Obstruction</td>
<td>-</td>
<td>D1 = 3.55m, D2 = 4.80m</td>
<td>-</td>
<td>D1 = 10.0m</td>
<td>-</td>
</tr>
<tr>
<td>Overlap hitpoint</td>
<td>50%</td>
<td>50%</td>
<td>25%</td>
<td>50% at 45° with D1&lt;5.5m, R=10m</td>
<td></td>
</tr>
<tr>
<td>Tests</td>
<td>12</td>
<td>10</td>
<td>12</td>
<td>13</td>
<td>6</td>
</tr>
<tr>
<td>Coverage (K)</td>
<td>22%</td>
<td>22%</td>
<td>11%</td>
<td>5%</td>
<td>0%</td>
</tr>
<tr>
<td>Coverage (SI)</td>
<td>22%</td>
<td>22%</td>
<td>11%</td>
<td>1%</td>
<td>3%</td>
</tr>
</tbody>
</table>

2.3 In-vehicle sensor and AEB system

All sensors are modelled as a perfect sensor with no dependency of the performance on other parameters, such as vehicle speed. In the current simulation tool the in-vehicle sensor system is represented by a single virtual sensor with several characteristic parameters. The ranges of these characteristic parameter values originate from reference simulations studies (Chajmowicz et al, 2019; Clepa, 2019; Gruber et al, 2019; Rosén, 2013; Seiniger et al, 2013; Seiniger & Gail, 2015; Uittenbogaard et al, 2016; Wimmer et al, 2019; Zhao et al, 2019), technical sensor specs and TNO's experience with sensors testing.

The sensor readings are transferred to an AEB logic in order to trigger the emergency brake. As in all reference simulation studies this is Time-to-Collision (TTC) based. A ray-tracing algorithm computes if the detection is going to enter a specified safety zone given the current relative distances and velocities and the time this will take. When the TTC drops below a certain value an emergency brake trigger is provided.

This fixed TTC value is in itself not enough to model an AEB system realistically since it will induce false positives. Some of the reference studies use a trigger width in which the target needs to be, while others only allow a brake trigger at a certain longitudinal distance. This simulation tool uses a Point Of No Return (PONR) method. Based on the current distance, velocity, theoretical maximum cyclist deceleration and a predicted time horizon of the cyclist, a moment can be computed at which the cyclist cannot prevent the collision anymore and will end up in the vehicle path. At this point the AEB logic is allowed to send the TTC based emergency brake trigger.

When an emergency brake trigger is received a longitudinal deceleration is initiated. The actuation delay is set at 0.2s. The deceleration shape is defined in a linear shape with a maximum deceleration of 0.9G and a constant jerk of 25m/s³. Both, again, are complying with the reference simulation studies and verification results.
The Euro NCAP cyclist AEB results from 2019 are used as a basis for defining the characteristic parameters for the different in-vehicle systems. This test series consist of a nearside crossing and longitudinal scenario. From the crossing scenario generally 4 different system behaviours can be seen:

- **S1**: No action at lower speeds and mitigation at higher speeds
- **S2**: Avoidance at lower speeds and mitigation at higher speeds
- **S3**: No action at lower speeds and avoidance at higher speeds
- **S4**: Avoidance at lower speeds and avoidance at higher speeds

For each of these behaviours a representative system is selected to be modelled by the simulation tool. The longitudinal scenario shows mostly avoidance at 60 km/h. For our fixed TTC-based AEB system, this means that the TTC trigger is set at 1.4s for all systems to be able to recreate this result. The final simulation setup for the 4 different systems can be found in Table 2. Note that system 4 is given an extra-large field of view to represent future systems.

**Table 2.** Simulation parameters used by the in-vehicle sensor models.

<table>
<thead>
<tr>
<th></th>
<th>S4 (Future)</th>
<th>S3</th>
<th>S2</th>
<th>S1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Field of view</td>
<td>+ - 90°</td>
<td>+ - 25°</td>
<td>+ - 50°</td>
<td>+ - 25°</td>
</tr>
<tr>
<td>Transparent</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Range</td>
<td>70m</td>
<td>50m</td>
<td>50m</td>
<td>50m</td>
</tr>
<tr>
<td>Frame rate (average delay)</td>
<td>50Hz (10ms)</td>
<td>25Hz (20ms)</td>
<td>10Hz (50ms)</td>
<td>10Hz (50ms)</td>
</tr>
<tr>
<td>Delay/latency</td>
<td>20ms</td>
<td>40ms</td>
<td>100ms</td>
<td>100ms</td>
</tr>
<tr>
<td>Mount</td>
<td>Middle - Windscreen 1.6m back</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Detection point</td>
<td>Reference Point</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Classification delay and detection**</td>
<td>100ms</td>
<td>200ms</td>
<td>500ms</td>
<td></td>
</tr>
<tr>
<td>Classification [50%]</td>
<td>Class. [100%]</td>
<td>Class. [100%]</td>
<td>Class. [100%]</td>
<td></td>
</tr>
<tr>
<td>Detection [50%]</td>
<td>Detect. [50%]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cyclist pred. time horizon</td>
<td>100ms</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cyclist braking deceleration</td>
<td>3m/s²</td>
<td>5m/s²</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**2.4 Communication sensor model**

In this study the focus is on 2 types of distinct messages communicated from the cyclist to the car. The first is the kinematic parameters (position, velocity, heading, etc) and the second is the prediction of the cyclist in the near future (including the classification as a cyclist). Since in this project only true positive scenarios (car and cyclist are going to be in a collision) are performed, this prediction can be translated in a ‘I am not changing my current state’ for a certain time horizon. Using thus a constant velocity for a larger time horizon increases the PONR and allows for earlier braking. A certainty of 94% can be achieved with a time horizon of 500ms and 1000ms (Meijer et al, 2017). After that the certainty level drops substantially (78% at 1.5s). A time horizon of 500ms is used in this study. Note that in an actual system a different approach can be taken where for example the actual path prediction could be communicated.

An indirect and direct communication method is selected to be simulated. Usually the indirect methods are high latency (40ms) forms of communication making use of interconnected base stations (e.g. Cellular 4G), making them unaffected by obstructions. The direct methods are most
of the time low latency (5ms) and the signals could be blocked by nearby obstructions. For that reason the direct method is simulated where it is either fully transparent (T) or fully obstructed (O). Additional latencies are added for all methods due to the 10Hz assumed frequency and a fixed total latency of 5ms for encoding, decoding, processing and security services (encryption/decryption) is taken into account. The distance between sender and receiver is not considered since the transmission range is in all case significantly larger than the area of interest.

The models described in terms of the simulation tool parameter can be found in the table below. In the simulation tool the communication sensor will be modelled in the same way as the in-vehicle sensor. The communication is used with 2 strategies; as a sensor or as preparation. In the sensor strategy the car is allowed the use the kinematic information of the communication to trigger the AEB. In the preparation strategy this is not allowed and the in-vehicle sensor needs to detect the cyclist itself as well. It does still benefits from the removal of the classification delay and cyclist prediction.

<table>
<thead>
<tr>
<th>Simulation Parameter</th>
<th>Indirect</th>
<th>Direct (T)</th>
<th>Direct (O)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Field of view</td>
<td>360°</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Transparent</td>
<td>Yes</td>
<td>No</td>
<td></td>
</tr>
<tr>
<td>Range*</td>
<td>100m</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frame rate (avr delay)</td>
<td>10Hz (50ms)</td>
<td>45ms</td>
<td>10ms</td>
</tr>
<tr>
<td>Cyclist prediction</td>
<td></td>
<td></td>
<td>500ms</td>
</tr>
<tr>
<td>Mount</td>
<td></td>
<td></td>
<td>Middle rear axle</td>
</tr>
<tr>
<td>Detection point</td>
<td></td>
<td></td>
<td>Reference Point</td>
</tr>
<tr>
<td>Classification delay</td>
<td></td>
<td></td>
<td>0ms</td>
</tr>
<tr>
<td>Classification and detection**</td>
<td></td>
<td></td>
<td>Classification [100%]</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Keep detection [100%]</td>
</tr>
</tbody>
</table>

2.5 Benefit analysis

The basis of this analysis is the impact speed of the car with the cyclist. Both the probability of a fatal and seriously injured cyclist can be expressed as a function of the impact speed (Chajmowicz et al, 2019). The Benefit (B) is computed using a standard method by the following formula:

$$B = 1 - \frac{\sum_{i=1}^{n} p_i(V_{AEB})w_i}{\sum_{i=1}^{n} p_i(V_{Ref})w_i}$$

Where \(n\) is the number of cases, \(p_i\) the probability on having a fatal or seriously injured outcome, \(V_{AEB}\), the impact speed when using an AEB system, \(V_{Ref}\), the reference (input) impact speed and \(w_i\) the weight factor for the \(i^{th}\) case. The weight factors represent the occurrence of said velocity for having a fatal or seriously injured accident as a part of all the simulations. These are based on the velocity distributions found in the CATS project (Uittenbogaard et al, 2015b).

3 RESULTS

The left plots in Figure 1 show this general benefit regarding fatalities (top) and seriously injured (bottom) cyclists for the different systems for the defined scenarios without communication. It shows that system 1 has the lowest benefit with ~59% for fatalities and ~20% for seriously injured cyclists. System 2 shows a benefit of ~80% for fatalities and ~81% for seriously injured cyclists. The latter is high due to its larger field of view which is beneficial for the crossing scenarios. System 3 lacks this large field of view, resulting in a lower benefit for seriously injured
cyclists (~31%). However it has lower delays than system 2, which is useful at higher speeds causing the fatalities, resulting in a benefit of ~83%. System 4, with the low delays and large field of view, shows a general benefit of ~92% for fatalities and ~99% for seriously injured cyclists.

The middle and right plots in Figure 1 show the general added benefit regarding fatalities and seriously injured cyclists for the different systems, communication methods and communication strategies. As can be seen the added benefit is highly dependent on the in-vehicle system and communication strategy. It is not substantially dependent on the communication method, since the difference was negligible in terms of delays for the AEB domain. Only when the communication was blocked by an obstruction, the added benefit for the fatal cases slightly lowered most relevant in the CVLBO scenario. When using the communication as a sensor the added benefit for fatal cases ranges from ~40% to ~5% (~5% less for the obstructed communication method) from system 1 up to 4, respectively. The field of view of the in-vehicle sensor is not substantially relevant, since most fatal accidents occur at higher car speeds. Mostly the classification delay, internal delays and larger assumed maximum cyclist deceleration allow for a larger added benefit from the communication sensor. For the seriously injured cyclist the benefit is either large (~70-80%, system 1 and 3) or small (~2-18%, system 4 and 2). This difference is caused by the smaller field of view for system 1 and 3, since the accidents with seriously injured cyclist occur mostly at lower speeds. When the communication is used as preparation the added benefit mostly drops for system 1 and 3 for the seriously injured cyclists, since the in-vehicle sensor needs to detect it as well with this strategy. For the other systems and all systems in the fatal accidents a drop of about 15% is observed compared to using communication as a sensor. Only system 1 and 2 still have an added benefit with this strategy. This is mostly due to the larger delays and larger assumed maximum cyclist deceleration used in the cyclist prediction computation in the crossing scenarios.

A sensitivity study into the time horizon of the cyclist prediction shows that increasing it had no extra benefit. Lowering it decreases the added benefit depending on the delays in the in-vehicle system. 500ms seems to be the most optimal value for the systems investigated in this study.
4 DISCUSSION

The non-future in-vehicle systems without communication (system 1-3) showed a 59% to 85% benefit for fatalities and ~19% to 81% for seriously injured cyclist. Reference literature showed a 35-59% benefit for fatalities (Rosen, 2013; Chajmowicz et al, 2019) and 14-54% (Chajmowicz et al, 2019) for seriously injured cyclists. This indicates that the non-communication results in this study are conservative and that the added benefit of communication is likely to be underestimated. One of the main reasons is that this study used the most common scenarios which are build up from accidentology to represent all real world accidents. Adding communication is expected to have a much larger benefit in the accidents that do not fit this average representation, but do occur in real life. For example, communication is expected to perform much better in scenarios with closer view blocking obstructions in the crossing scenario or accidents where a cyclist makes a manoeuvre towards the car which cannot be predicted from the in-vehicle sensors. To strengthen the conclusion from this study, it is recommended to perform this simulation study with a real-world accident scenario dataset as was done in (Rosen, 2013; Chajmowicz et al, 2019).

Although communication shows the most added benefit for certain in-vehicle systems, it can have an indirect benefit for other systems as well. For instance, the high performance of certain systems could have been reached by allowing a higher false positive rate. Adding communication will keep the high performance while lowering the false positives. Moreover, it could be that adding communication as an input will be more cost-effective than adding more in-vehicle sensors and investing in algorithm development to achieve a higher performance. This, however, should be investigated.

Finally, as mentioned in the introduction, the added benefit of communication was only studied in the AEB domain and it will clearly have additional benefits in other driver assistance tasks.

For the results of this study some relevant assumptions were made. Although a part of the accuracy (fixed single bias) of the communication sensor was investigated, the main study used perfect sensors for both the communication and in-vehicle sensors. Actual sensors will always have an non-zero accuracy and be probabilistic in nature. This not only includes the kinematic parameters, but also the cyclist prediction. Since in this study only positive scenarios are investigated, the cyclist prediction is implemented in the PONR computation that the state (constant velocity and heading) will not change. In actual systems a path prediction is more likely to be used for the car to determine its actions. It should be noted that the cyclist prediction needs a high degree of certainty and accuracy to be practical in real life.

The AEB logic is modelled independent of any vehicle or communication inputs and only checks the TTC and PONR. Actual systems may, for example, also be influenced by the vehicle speed by braking later at lower speeds. Also the AEB emergency braking system is modelled in a simplified way. It will ramp up to the maximum deceleration in a fixed time until the car is stopped. Actual systems can have a multi-stage approach, starting with a lower deceleration before using the full braking power.

5 CONCLUSIONS

In this study the benefit of a cyclist to car communication in AEB scenarios has been investigated. A simulation environment was created in which an standard AEB logic is modelled. 4 different AEB systems have been created based on current systems found on the market today, where the field of view was increased substantially for the best performing one to represent a future AEB system. Next to that 3 different communication methods with 2 different strategies were defined based on current technology. All combinations of these systems were subjected to the
most common car to cyclist accidents found in accidentology. The benefit of adding
communication was computed based on saved lives and prevented serious injuries.

The results show that adding communication is most beneficial for in-vehicle systems with large
classification- and internal delays. To achieve a high total benefit, a large field of view is also
needed if the preparation strategy is used instead of the sensor strategy.

All in all it can be concluded that this study provided a clear indication that adding
communication in AEB scenarios can have a substantial added benefit.

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