

# Cyclist Collision Avoidance Using Imagery Sensor

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# Contents

<b>1</b>	<b>Summary</b>	<b>3</b>
<b>2</b>	<b>Sammanfattning på svenska</b>	<b>3</b>
<b>3</b>	<b>Background</b>	<b>4</b>
<b>4</b>	<b>Purpose, research questions and method</b>	<b>4</b>
<b>5</b>	<b>Objective</b>	<b>5</b>
<b>6</b>	<b>Results and deliverables</b>	<b>6</b>
6.1	An algorithm for detecting and tracking bicycles . . . . .	6
6.2	A database with emergency brake distance distributions for different bicycle/rider types . . . . .	7
6.2.1	Method . . . . .	7
6.2.2	Results . . . . .	7
6.3	A feasibility study for detecting bicycle's orientation . . . . .	9
6.4	A feasibility study for detecting a cyclist's intention . . . . .	10
6.5	Euro NCAP demonstration . . . . .	11
6.6	A collision avoidance strategy . . . . .	12
6.7	Real life benefit estimation . . . . .	13
6.7.1	Method . . . . .	13
6.7.2	Results . . . . .	14
<b>7</b>	<b>Dissemination and publications</b>	<b>14</b>
7.1	Dissemination . . . . .	14
7.2	Publications . . . . .	14
<b>8</b>	<b>Conclusions and future research</b>	<b>15</b>
<b>9</b>	<b>Participating parties and contact persons</b>	<b>16</b>

**FFI in short** FFI is a partnership between the Swedish government and automotive industry for joint funding of research, innovation and development concentrating on Climate & Environment and Safety. FFI has R&D activities worth approx. €100 million per year, of which about €40 is governmental funding. Currently there are five collaboration programs: Electronics, Software and Communication, Energy and Environment, Traffic Safety and Automated Vehicles, Sustainable Production, Efficient and Connected Transport systems. For more information: [www.vinnova.se/ffi](http://www.vinnova.se/ffi)

# 1 Summary

Collision avoidance within active safety has so far mainly focused on vehicle-to-vehicle and vehicle-to-pedestrians. Bicyclist accidents are getting more attention and with the introduction of the EU-NCAP protocol 2018 starting to be more addressed. Historically, research around avoiding cyclist accidents has been underrepresented which this project was trying to address.

Some of challenges with avoiding cyclist accidents are their mobility (like pedestrians they can change direction quickly compared to vehicles and take, for the driver, unexpected paths) and higher speed compared to pedestrians. Especially cyclists turning are difficult to predict by state-of-the-art systems.

The project consortium with Veoneer, Linköping University, Zenuity, VTI and Autoliv has showed an estimated potential to reduce the number of cyclist accidents and fatalities by half with active safety systems designed towards cyclists. This project has shown that with a wider field-of-view vision sensor, by detecting cyclist+bike as one entity and tracking an AEB-system can be effective according results in EU-NCAP testing. Also, research studies for path prediction was carried out in the project. One study showed braking capabilities in different moisture conditions and cycle types. Another by wheel orientation by fitting ellipses to solve most of the bicycle state space parameters. The third was gesture recognition by DNN for intention interpretation to predict the cyclist movement.

Some challenges remain as subjects for future research such as variation in cycle types, occlusions, night time and adverse weather conditions which would be subject for further research.

## 2 Sammanfattning på svenska

Inom trafiksäkerhet för aktiva säkerhetssystem har fokus huvudsakligen legat på bilkollisioner samt fotgängare. Nu öka fokus på olyckor med cyklister och introduktionen av EuroNCAP-protokoll gör att system kommer ut på marknaden. Historiskt har forskning på området varit underrepresenterat vilket det här projektet delvis försöker förbättra.

Några utmaningar med att undvika olyckor med cyklister är deras rörlighet (jämförbart med fotgängare kan de ändra riktning snabbt jämfört med fordon och ta rörelsebanor som är oväntade för förare) och att de kan röra sig relativt fort jämfört med fotgängare. Särskilt svårt är när cyklar svänger vilket är svårt för dagens system att prediktera cykelns färd bana.

Projektkonsortiet med Veoneer, Linköpings universitet, Zenuity, VTI och Autoliv har visat en potential att reducera numret av omkomna cyklister i trafiken. Detta genom ett aktivt säkerhetssystem specifikt designat för undvika cyklistolyckor. Projektet har visat att med en kamera med vidvinkel, en algoritm som detekterar cyklist+cykel som en enhet och med objekttrackning har visats vara kraftfullt genom toppresultat i EU-NCAP-provning. Förstudier har också gjorts på prediktion av färdväg under projektet. En studie har visat cyklisters förmåga att bromsa i kritiska situationer med olika cykeltyper i olika förhållanden. En annan studie har visat hur hjulriktning kan bestämmas med att ellipser löser de mesta tillståndsparametrarna för en rörelsemodell. En tredje studie har visat hur DNN kan göra gestigenkänning som kan användas för att tolka intentioner för förstå vad en cyklist planerar att göra.

Några utmaningar kvarstår som mer variation av cykeltyper, skymd sikt, mörkers inverkan och dåligt väder som kan vara uppslag för framtida forskning i ämnet.

### 3 Background

While fatality rates for occupants of motorized vehicles have steadily declined in Europe, the apportionment of cyclists increased from 6% in 2007 to 8% in 2016 according to European accident statistics ([www.erso.eu](http://www.erso.eu)). Reducing car-to-bicycle crashes is still very important because of the societal cost accrued each year for this type of crashes. A study on Swedish accident data by Fredriksson et al. [2] showed that the most common injurious car-to-cyclist accidents in Sweden occurred when the cyclist was crossing a road (from left or right) where the car is driving straight. This was found to be most common in urban areas where the traffic situations can be complex. For fatal accidents it was then followed by a scenario where the car was passing a cyclist on a straight rural road and the cyclist turned in front of the car. For injured cyclists it was followed by a scenario where the car was turning left and the cyclist was crossing the road that the car was turning into from right side, a typical urban junction scenario. In all four scenarios daylight and dry conditions were dominating. These four scenarios represented around 70% of all accident scenarios for both AIS2+ and fatally injured cyclists in Sweden.

There are several collision avoidance and mitigation systems on the market, and the first systems for pedestrian protection are currently appearing in terms of driver alert, automated braking, automated steering maneuvers, hood lifters and external airbags. The driver assistance systems can highlight the presence of pedestrians, warn the driver, and autonomously brake or steer away the car to avoid or mitigate a collision. As a last resort, when the collision is unavoidable, passive safety systems such as hood lifters and external airbags in front of the rigid front structures (such as the bonnet leading edge or A-pillars) can be deployed to mitigate the injury outcome.

Cyclists are a group of vulnerable road users, for whom much less has been done so far. However, the avoidance and injury mitigation principles for pedestrians can be applied once a good detection and tracking filter is developed. To enable faster introduction of collision avoidance systems designed for cyclists, the European New Car Assessment Program (EuroNCAP) was at the point of starting the project planning to include the first bicycle test protocols in 2018. The inclusion of cyclist scenarios in consumer ratings is believed to promote automated emergency braking (AEB) for car-to-bicycle interactions. However, the first implementation was limited to two scenarios. In addition, cyclists are together with other types of vulnerable road users, a challenge for autonomous driving where safe interaction between autonomous vehicles and cyclists needs to be developed.

### 4 Purpose, research questions and method

Showing how improved capabilities can avoid cyclist accidents could be used to improve AEB systems and influence future Euro-NCAP testing protocols. This project aims to improve the existing technology for detecting, tracking and predicting cyclists using an imagery sensor mounted on a vehicle and demonstrate this improved development.

The main research questions for this project are:

- How can improved understanding of cyclist capabilities, behavior and interpretation of intentions be used for preventing cyclist accidents?

- How could improved cyclist detection and ADAS algorithms give a real life benefit?

The project had the following method for the work flow. Firstly, an image dataset was collected by Veoneer partly with the previous generation vision system with 52° field-of-view and partly with the new generation with a wider field of view sensor (100°), 1. This dataset was used in the development project (WP1). Secondly, a controlled empirical study was carried out by VTI to study cyclists' behaviour with regard to braking capability (WP2). Thirdly, the task of improved object detection and tracking of was divided into two parts; non-maneuvering cyclists and maneuvering cyclists in daylight and night time conditions (EuroNCAP 2018 and beyond). This was done by Veoneer in WP3 and interacted with parallel work in WP4 and WP5. In parallel with WP3 the task of detecting and tracking maneuvering cyclists was carried out. For such a tracking algorithm detection of cyclist intention and prediction to maneuver is crucial. Two methods for prediction cyclists' movements was studied in parallel; In WP4 the cyclist's prediction to maneuver was detected from the inclination of the bicycle and the articulation of the wheel which was measured from image data using ellipse extraction algorithms. This task was carried out at LiU. In WP5 the cyclist's intention to maneuver was detected from the cyclist's body posture and gestures using trained classifiers. This task was carried out by Zenuity. In WP6 a tracking algorithm was worked on to track multiple cyclists by LiU. Finally, in WP7 results will be evaluated, integrated and demonstrated in a vehicle. An estimated real-life benefit based on the different work packages was done.



Figure 1: Veoneer camera

## 5 Objective

The objective of the project was to (1) Contribute to the Vision Zero by increasing active safety features that are capable of reducing and mitigating car-to-bicycle crashes. (2) Increase knowledge about stopping distance distributions for different bicycle/rider types in an emergency situation. (3) Explore possibilities to detect cyclist intention

for extended protection in relevant cases beyond EuroNCAP 2018. (4) Develop new and enhance existing technology and algorithms to reach cyclist protection beyond the EuroNCAP 2018 requirements. (5) Increase innovation power within Swedish automotive industry which in this project was represented by Veoneer and Zenuity. (6) Promote the cooperation between industry, academia and a governmental research institute by bringing VTI, LiU and Veoneer together under the same project.

## 6 Results and deliverables

### 6.1 An algorithm for detecting and tracking bicycles

Computer vision algorithms was developed to classify bike and cyclist as one entity. It consists of a classifier that separates pedestrian from a person riding on the bicycle. It also contains a classification-based separator that separates pedestrians and bicyclists. It contains a classifier that detects bicycle wheels. Finally, a tracker that combines pedestrian measurements and bicycle wheel measurements. The results can be seen in Figure 2.

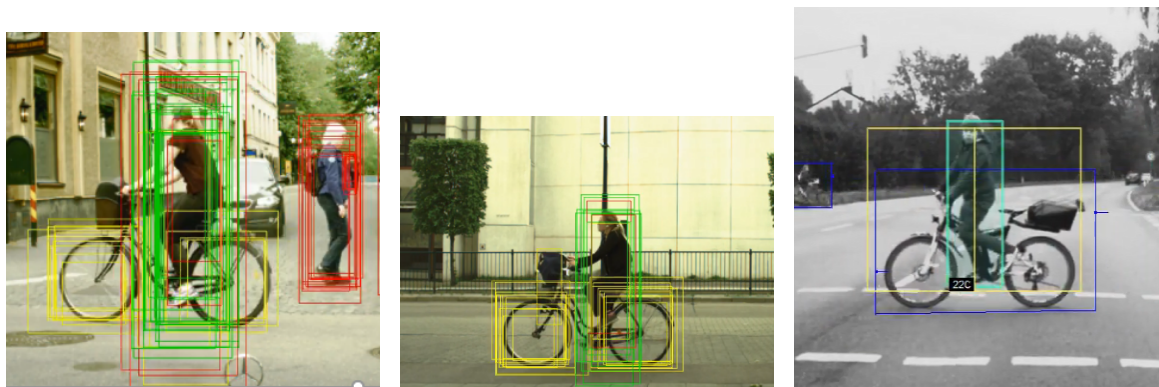


Figure 2: a) Pedestrian separator b) Wheel detection c) Bicycle tracking

A dynamic model for the bicycle is used for tracking. The following state vector with parameters are determined and processed:

- State vector
  - Longitudinal, lateral and vertical position,  $p$
  - Longitudinal and lateral velocity,  $v$
  - Tune process noise to make longitudinal velocity “constant”
- Parameters
  - Wheel radius,  $r$
  - Distance between the naves,  $b$
  - Distance from center of wheel to center of cyclist,  $d$
  - Distance from ground to bottom of cyclist,  $g$
  - Height of cyclist,  $h$

The parameters are visualized in Figure 3. Also, the initialization of some variables was done to be able to start the tracker before the complete bicycle could be visible.

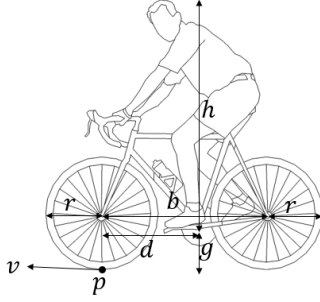


Figure 3: A dynamic model

## 6.2 A database with emergency brake distance distributions for different bicycle/rider types

### 6.2.1 Method

A controlled empirical study with 32 recruited participants has been carried out at the Swedish road and transport research institute (VTI, [www.vti.se](http://www.vti.se)) in which the emergency stopping distance was measured. Factors such as cyclist type, bicycle type, brake type, approach speed, and road surface (dry and wet asphalt) were investigated.

	Fast N=8	Normal N=12	Comfort N=6	Electric N=6
Male/female	7/1	9/3	6/0	5/1
Mean age (SD)	36.3 (10.5)	50.5 (11.9)	63.0 (12.8)	52.0 (10.3)
Mean cycling days/week	1.5 (0.5)	1.8 (0.9)	2.3 (1.4)	1.3 (0.5)

Table 1: Participants in the study

To collect data from different cyclist types and bicycle types, participants were recruited by a web questionnaire, where they answered questions about cycling habits and bicycle type. From this, the following four cyclist categories were created, and participants sorted into these: Fast, Normal, Comfort, Electric bicycle. See Table ??.

The test track was a selected area at the backyard at VTI, long enough for participants to accelerate to the requested speeds and free from cavities or other obstacles. The surface was asphalt which was swept before data collection. The track consisted of one acceleration section of approximately 80 meters and two parallel measurement sections of approximately 30 meters, one dry and one wet, 4.

### 6.2.2 Results

Every cyclist used rear wheel brake and most of them also used front wheel brake. Analyzing only those who used both brakes, the average retardation was 4.29 m/s<sup>2</sup>. All other results were about unchanged. Analyzing those who used rear wheel brake only, the retardation was 2.47 m/s<sup>2</sup>. There was only 4 persons in this group. The difference, the additional retardation by adding front wheel brake, is about 1.9 m/s<sup>2</sup>.

The reaction time was 0.386 s and 0.458 s respectively for those who used both brakes and those who used only rear wheel brake. Again, this is likely a difference between cyclist types rather than a difference between brakes. Possibly the estimating procedure also identifies the break time differently, if the break is sharper when using both brakes.



Figure 4: Test track in the backyard at VTI

This is regarded a comparison of cyclist types, those who add front wheel brake and those who do not, but it cannot be regarded a pure effect of adding the front wheel brake because other properties like biking habits, choice of bike etc. will also have some effect on how the brakes are used and, possibly, brake quality. In Table 2 the mean values of stopping distances for cyclist types and bicycle types are presented.

Target speed	Bicycle types	Surface		Cyclist types	Surface	
		dry	Wet		dry	wet
15 km/h	Mountain Bike	3.3	3.4	Fast	3.6	3.7
	Racer bike	2.9	3.5	Normal	4.2	4.3
	City bike	4.1	3.8	Comfort	4.0	3.8
	Electric bike	3.8	4.1	Electric	3.8	4.1
	Comfort bike	4.6	4.7			
20 km/h	Mountain Bike	5.9	5.5	Fast	5.8	5.4
	Racer bike	3.8	6.2	Normal	7.0	7.5
	City bike	6.4	6.3	Comfort	5.9	6.1
	Electric bike	6.0	5.9	Electric	6.0	5.9
	Comfort bike	7.0	7.6			
25 km/h	Mountain Bike	8.2	7.9	Fast	8.2	7.8
	Racer bike	7.4	7.3	Normal	10.2	11.0
	City bike	9.0	8.6	Comfort	8.5	8.9
	Electric bike	8.5	8.7	Electric	8.5	8.7
	Comfort bike	10.1	11.4			
30 km/h	Mountain Bike	11.2	10.4	Fast	10.2	10.3
	Racer bike	10.5	12.9	Normal	13.5	13.7
	City bike	12.8	12.5	Comfort	11.8	14.5
	Electric bike	11.2	12.1	Electric	11.2	12.1
	Comfort bike	12.1	13.6		-	-

Table 2: Mean values of stopping distances [m]



The difference in retardation between dry and wet asphalt is small (3%), however it is important to note that the rim brakes were not wet and therefore the wet condition is not comparable with a rainy day. The effect of speed on retardation is small. The stopping distance is almost the same for different bicycle types. There is a large difference in stopping distance between cyclists using one or two brakes, however this is a factor that would be hard to detect for a camera-based safety system. The personality, reflected by cyclist type, is an important underlying factor affecting the stopping distance.

### 6.3 A feasibility study for detecting bicycle’s orientation

To be able to estimate the orientation of a bicycle, it needs to be mapped from the image/sensor plane to a global coordinate system. This mapping was proposed in [9] that relies on detecting ellipses to the bicycle’s wheels in the image plane and utilize ellipses parameters to infer the mapping to the global coordinate system. For demonstrating their approach, they used a special setup of a bicycle with reflective wheels that is captured in a very dark environment. However, they have no approach for detecting ellipses in the wild in uncontrolled environments.

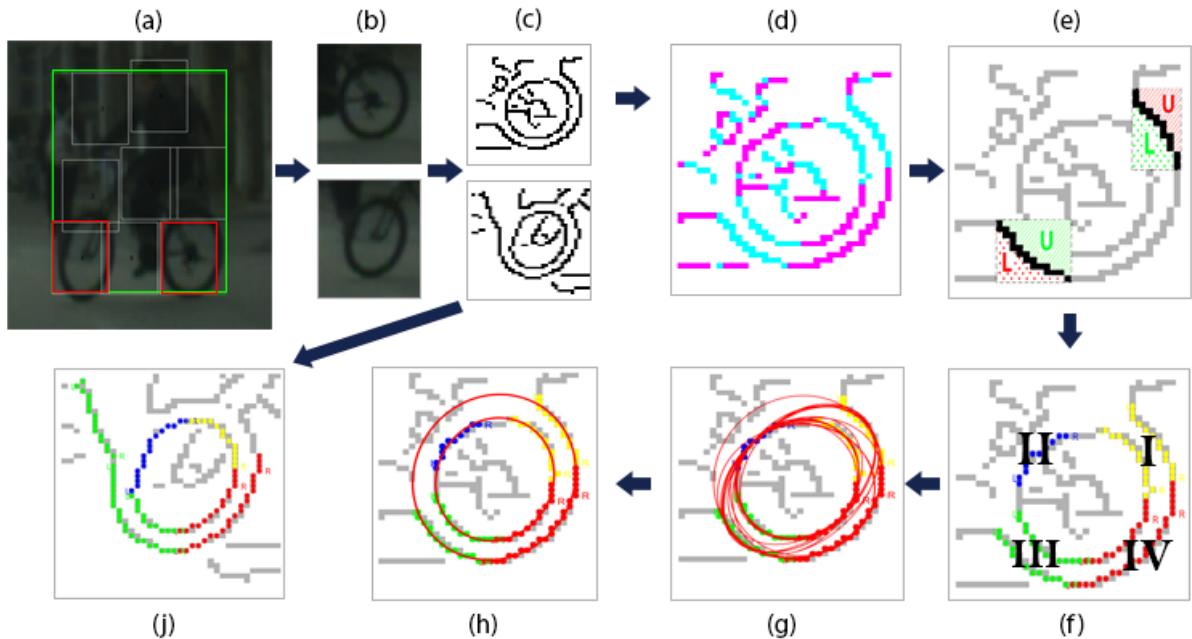


Figure 5: An overview for the ellipse detection algorithm that is produced from WP5.

We investigate the problem of fitting ellipses to bicycles’ wheels in real driving scenarios using a publicly available dataset. An overview of our proposed approach is shown in Figure 5. We utilize a robust detector called the deformable parts model [10] to detect the cyclist. Then, image patches around the wheels are extracted based on the parts-model given by the detector. Afterwards, we apply edge detection, preprocessing and grouping of edge points into arcs. Different groups of arcs are used to fit ellipse hypotheses. Finally, we evaluate these hypotheses and select the best ellipse based on how they comply to the edge map. More details about the method can be found in our published work [11].

To evaluate the potential of the proposed ellipse detection algorithm, we create a simple decision tree to determine either a cyclist is turning left, right or driving straight only by looking at the ellipse parameters. Experiments on a sample of the test track

recordings shows that the detected ellipses can reliably help inferring the orientation of the cyclists even with a simple decision tree. Few examples for the outcome of this experiment is shown in Figure 6.



Figure 6: Bicycle orientation estimation based on the proposed ellipse detector and a simple decision tree.

#### 6.4 A feasibility study for detecting a cyclist’s intention

In order to train DNN for recognizing gestures some annotated data was needed. In the project one activity was to annotate a limited dataset in order to perform a feasibility study. The results can be seen in table ?? . From here it was decided to focus on the turn gesture and when the cyclist is looking at the vehicle since these are linked to when the cyclist is in motion (most relevant for collision avoidance).

Left arm raised	9
Right arm raised	10
Looking back	5
Looking sideways	21
Waiting (stop sign/zebra crossing)	26
Stops pedaling	7
No action	2
Foot down	98
Foot up	30
Cyclist leaning	7
Cyclist slowing down	1
Cyclist standing up	0

Table 3: Annotation of cyclist gestures signaling intention

We investigate detection of two common signals for maneuvers: i) raising of an arm; and ii) turning the head towards the ego vehicle. The task is challenging in the wild, as the in-class variation is very large in terms of pose, lighting, scale, aspect ratio, and appearance. We found that despite these signals being common, for instance around any (Swedish) university, the case is fairly rare in typical data sets. We collected images of cyclists from a large Veoneer dataset, and annotated each image with whether the arm is raised and whether the head is turned towards the ego vehicle. The total is 13 positive and 29 negative images for the raised-arm signal, and 32 positive and 75 negative images for the looking-at-ego-vehicle signal. Due to the small size of the data sets, we try to utilize methods trained on larger data sets to extract features, and a simple classifier on top of that. Some qualitative results are shown in fig. 7.

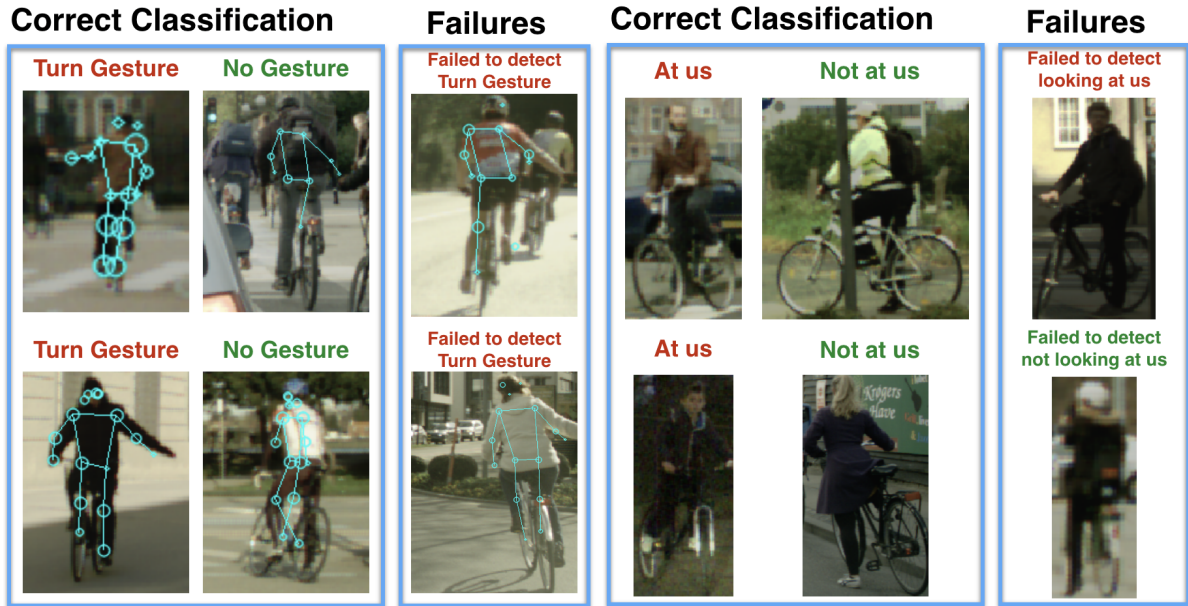


Figure 7: Examples of output from the algorithm. For the arm-raised signal (left) we overlay the output of the feature extractor, PoseNet, on the image. For the look-at-us signal (right) we utilize the ResNet18 feature extractor which output is harder to concisely visualize.

For the raised-arm signal, we first employ PoseNet to extract keypoints of the cyclist. PoseNet fails occasionally, for instance when the cyclist is in too low resolution. We utilize only the samples where PoseNet succeeds, 10 positive and 22 negative. We use a multivariate normal classifier on top of the keypoints extracted by PoseNet. We use 4 positive, and 6 negative samples for testing, and the rest for training. The results vary depending on the exact train/test split, but the accuracy is better than chance. In order to obtain a more accurate method and conduct a more thorough evaluation, more data is required.

For the looking-at-ego-vehicle signal, we instead extract features with a ResNet18 pre-trained on ImageNet. We experimented with features from different layers of the residual network, and with how to collect the image features into a single feature vector. We found picking the center feature from layer2 (the stride 8 block) to work best. The downside of this approach, in contrast to relying on PoseNet, is that the features are very high dimensional here. However, we were unable to reliably estimate the head pose with PoseNet. Based on the features, we construct a multivariate normal classifier. The dataset is partitioned into train- and test parts. The test part contains 7 positive and 15 negative samples. The accuracy varies due to the small size of the test set, but typically ranges between 50% and 60%. For future work, more data is required.

## 6.5 Euro NCAP demonstration

For the wider field-of-view sensor, detection and tracking algorithm the demonstration of AEB was conducted for the EU-NCAP scenarios. The algorithms were implemented on an existing automotive grade platform and experiments was conducted on test track. First the 2018 lateral scenario was shown with a selected frame and a birds view from the vision system with the object, here shown in 8. But also, the planned scenarios for

2020 was successfully demonstrated as well, here can be seen in 9 and ??.



Figure 8: Demonstration of EU-NCAP 2018 scenario

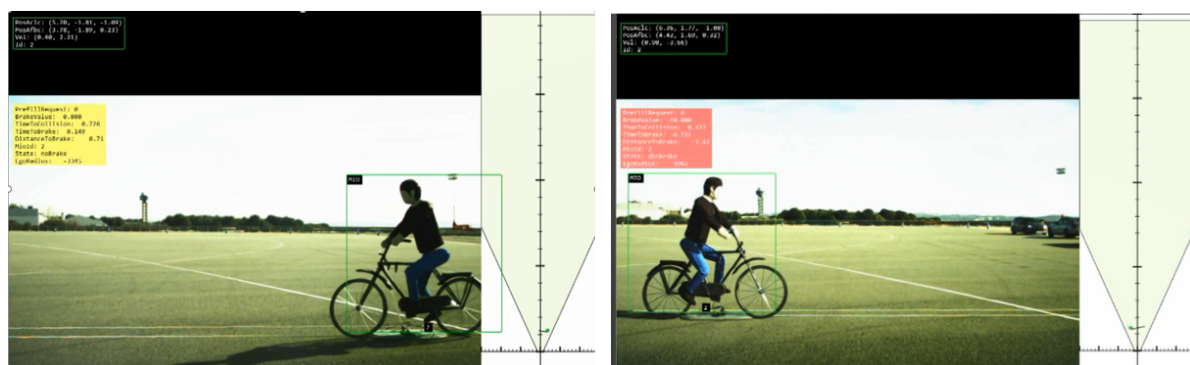


Figure 9: Demonstration of EU-NCAP 2020 potential scenarios, with occlusion and from left

## 6.6 A collision avoidance strategy

The strategy to avoid cyclist accidents is to as early as possibly know, with a high probability, whether the cyclist's future path will cross the vehicle's future path or not. Then active safety systems can then be designed to avoid, or mitigate, accidents by either braking, steering or increasing awareness for the driver dependent what is best in the given situation.

A better understanding by a wider field-of-view, brake capabilities data base, classification and tracking of cyclists, path prediction and gesture recognition will give relevant input for a threat assessment algorithm. Combining all components for an active safety system.

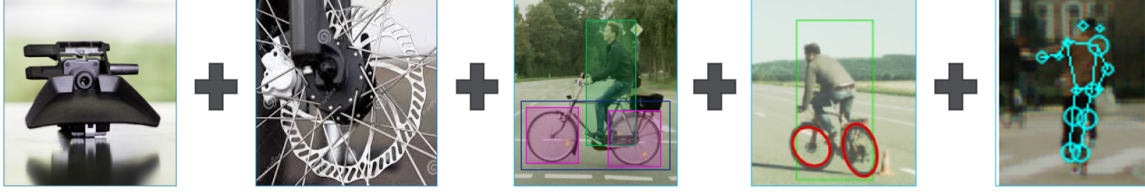


Figure 10: An combined strategy

## 6.7 Real life benefit estimation

### 6.7.1 Method

Recent effectiveness studies on ADAS functions by Lubbe et al. [4] on German In-Depth Accident Database (GIDAS) [5] shows the safety benefit of different ADAS technologies in combination with passive safety technology. The analyses assumed 100% implementation of all the technologies in the passenger cars.

Previous study carried on GIDAS estimated that AEB - cyclist prevents between 6-84% of the fatalities in crashes with passenger cars [6] and most recent study shows estimates the effectiveness of AEB – cyclist to 22.2% [4]. The study included the rule set for AEB - cyclist, AEB would address both crossing and longitudinal cyclist accidents, between speed range greater than 5kmph and less than 40kmph. Cyclist speed was less than 30kmph with no visual obstruction.

To estimate the effectiveness on accidents, first the new imagery system was considered. The increase in field-of-view to  $100^\circ$  has big influence but also the increased capability by classifying and tracking cyclists. The estimation, aided with results from [6], is that an addition of  $\sim 17\%$  would be avoided.

When it comes to the results of different bikes braking capabilities and their stopping distances another estimation needs to be done. Knowing the latest point in time-space when a bike can brake to avoid crash, but also the braking profile, can improve the prediction and especially reduce conservative approaches to manage false positives. Similar study evaluating the difference between e-bikes and traditional bikes highlights the difference in cyclist behavior and the way cyclist interact with other road users change when switching between different bikes (e-bikes and traditional bikes)[7]. The study also highlights that it is harder to predict the movement of the cyclists. Thus, we think by including the results of VTI study carried out in Linköping testing grounds will improve the working of AEB by  $\sim 10\%$  based our optimistic estimation.

One difficult part with cyclists is when they turn, their path prediction changes relatively much. Hence a system that can predict path by turning will have an increased effectiveness since these are among the most common accident types [2]. The results from ellipse extraction and solving the state-space variables for tracking could do that and predict turning. The estimation is that this will give an extra  $\sim 10\%$  in effectiveness.

One of the shortcoming of either ADAS or automated driving is the uncertainty arising from sensor data and the fact that intention of human cyclist or drivers cannot be easily measured [8]. One of the work packages of CYCLA tried to address this issue by understanding and building an algorithm to understand the intention of the cyclist and incorporating that into AEB we think will address some of the remaining fatalities. This was estimated to be  $\sim 15\%$ .

## 6.7.2 Results

The estimated AEB - cyclist from literature was used to quantify the results of different work packages from this project in terms of number of cyclist's lives saved. 22% was used as a baseline estimate, which was then used to estimate the number of cyclist fatalities that could be prevented by AEB with the improved detection, understanding cyclist braking capabilities, and cyclist turning indication and intention prediction. By using the equation below, we get the number of lives saved by different suggested improvements. The improvement/results of the studies were added in steps and the estimated effectiveness was applied only to residuals (meaning remaining cyclist fatalities).

$$\text{Number of lives saved} = \text{Effectiveness} * \text{number of remaining fatalities}$$

Table 4 shows the estimated improvement of different variables included in the project and the number of cyclist fatalities saved by implementing these improvements.

Variables	Estimated reduction	Number of fatalities	Cyclist lives saved
Cyclist fatalities in 2018		40500	
AEB cyclist	~22%	26152	8991
Improved detection of cyclist	~17%	23537	5357
Improved understanding of cyclist braking capabilities	~10%	21184	2615
Cyclist turning prediction	~10%	18006	2354
Cyclist intention	~15%	26152	3178

Table 4: Estimated reduction in fatalities by implementing results from the work packages

## 7 Dissemination and publications

### 7.1 Dissemination

The project was presented at the FFI annual results conference 2019-09-17 in Gothenburg which had the theme on the strategic cyclist focus drive. In 2017 the project was also presented at SAFER, Chalmers for the reference group "Systems for accident prevention and AD" where the recommendation was to associate the project with SAFER. Also, some results have been presented at international scientific conferences, such as Conference on Computer Analysis of Images and Patterns 2017, Fusion 2017, and BMVC 2018. The latter work has lately been accepted in the top-tier journal TPAMI and some project results found their way into a book on visual feature representations.

### 7.2 Publications

- Eldesokey, A., Felsberg, M., & Khan, F. S.: Ellipse Detection for Visual Cyclists Analysis 'In the Wild'. In Computer Analysis of Images and Patterns: 17th International Conference (2017). [https://doi.org/10.1007/978-3-319-64689-3\\_26](https://doi.org/10.1007/978-3-319-64689-3_26)

Table 5: Dissemination

How are the project results planned to be used and disseminated?	Mark with X	Comment
Increase knowledge in the field	X	Results and discussions has resulted in increased knowledge and sharing for both academia and industry
Be passed on to product development projects	X	People in the development project was directly involved in the project and could directly utilize some results in development project
Introduced on the market	X	Some of the results, WP3, was already introduced to the market and tested at EU-NCAP with top scores
Used in investigations / regulatory / licensing / political decisions		

- Skoglund, M. A., Sjanic, Z., & Kok, M.: On orientation estimation using iterative methods in Euclidean space. In Proceedings of the 20th International Conference on Information Fusion (2017). <https://doi.org/10.23919/ICIF.2017.8009830>
- Felsberg, M.: Probabilistic and biologically inspired feature representations. Synthesis Lectures on Computer Vision. San Rafael: Morgan & Claypool Publishers (2018). <https://doi.org/10.2200/S00851ED1V01Y201804COV016>
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## 8 Conclusions and future research

There is a substantial potential in saving lives with advanced cyclist collision avoidance systems. The imagery sensor provides suitable data in order to develop algorithms that can improve detection, classification and prediction this work has shown. Real life benefits have been estimated to half the number of cyclist accidents with light vehicles.

However real-life variance of cyclist types, adverse weather and occlusions are problems that still needs further research. When this research project started electric scooters were not that common compared to today. Also, other different kinds of powered two-wheeler are increasing in numbers on the streets also providing a challenge.

One specific future research item could be to investigate a deep-learning approach that jointly detect cyclists and ellipses for the wheels. The inherent feature representation for the object detection in deep network can be very beneficial for fitting ellipses as well.

## 9 Participating parties and contact persons

### Partner companies

The project consortium started with Autoliv as coordinator, Linköping University & VTI. When Zenuity was founded as an joint venture between Autoliv and Volvo Cars, the relevance for WP5 made the consortium decide to invite them. Then Veoneer was formed as a spin-off from Autoliv with the active safety business, the coordination was transferred with that.



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