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Active Safety for Car-to-Bicyclist Accidents

Master's Thesis in Engineering Mathematics and Computational Science

ARIAN RANJBAR

Department of Mathematical Sciences

Division of Mathematical Statistics

Chalmers University of Technology
Gothenburg, Sweden 2014

Abstract

During the last years the rapid development of countermeasures has led to an overall decreasing number of fatalities in road traffic accidents. However, the positive trend does not hold at the same rate for bicyclists. It is therefore desireable to investigate these type of accidents and discuss possible countermeasures.

In this work the car-to-bicyclist accidents were studied to understand the context in which they occur. Data was collected from the German In-Depth Accident Study (GIDAS) database and the Pre-Crash Matrix (PCM) extension which contained reconstructed accidents. A geometrical classification method was developed to find the most common type of accident scenarios and descriptive statistics was gathered. Further on, a risk model was derived to find the probability of an accident to result in severe injuries. The model was also used to calculate the theoretical effectiveness of a simplified Autonomous Emergency Braking (AEB) system.

The study showed that the most common car-to-bicyclist accidents were lateral and longitudinal scenarios in intersections, where the car was travelling straight forward. This was also connected to the risk analysis which showed that the most risk influencing parameter was the impact speed of the car in the collision. Finally, the effectiveness study indicated that AEB has a considerable potential to mitigate car-to-bicyclist accidents.

Acknowledgements

I would like to thank my advisor Dr. Erik Rosén without whose support, advice and helpful discussions this thesis would not have been possible. I also wish to express my gratitude towards Autoliv Research AB for letting me do my thesis work there. Finally I extend thanks to my supervisor at Chalmers University of Technology, Prof. Olle Nerman for providing guidance and feedback throughout the project.

Arian Ranjbar, Gothenburg 7/12 2014

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Introduction

1.1 Background

Road traffic accidents are listed as one of the ten largest global health problems, claiming approximately 1.2 million lives per year.[1] In Europe the rapid development of countermeasures has led to a decreasing number of fatalities in road traffic accidents. However, the positive trend does not hold at the same rate for bicyclists. The reason is belived to be an ongoing increase in popularity for bicycling, giving a larger propotion of bicyclists on the road.[2]

Several countermeasures have been developed or are in development with the goal to prevent and mitigate the accidents between cars and vulnerable road users. The different types of countermeasures are often divided into two categories, active and passive. Active safety systems aim to avoid or mitigate collisions whereas passive safety aim to lessen injuries once a collision is unavoidable. The latter type of systems has allready been on the market for some years, but recently the automotive industry have started to also develop and implement active safety systems.

Common for these types of active safety systems is the use of different types of vision sensors, such as camera and radar, to track traffic participants and perform real time estimastes of traffic situations. If the system judge that a critical situation is developing, with no action taken from the driver, it may interact with the driver or directly through the steering of the car.

To increase the devlopment of active safety systems for car-to-bicyclist accidents, Euro NCAP plan to include AEB (Autonomous Emergency Braking) system for this particular scenario in their star rating 2018.[3] To approach the problem an investigation of bicycle accidents is desired. In particular to study real world accidents to find common type of scenarios an active safety system will have to adress.

1.2 Aim

The aim of this project is to identify possible active safety solutions for car-to-bicycle accidents that aim to avoid or mitigate such accidents. This will be done in three steps. First a study of car-to-bicyclist accidents will be done, to understand the context in which the accidents occur. The focus will be on situational parameters that are particularly relevant for the car-based active safety systems. In the second part a risk analysis will be done on the car-to-bicyclist accidents to understand the most influencing risk parameters, which is crucial to predict the benefit of any proposed system. Finally, possible solutions will be discussed based on the previous studies.

1.3 Limitation

No new system concepts will be devloped. The project focuses on the study of car-to-bicyclist accidents by statistical tools. Applicability will only be discussed for known types of technologies.

1.4 Specification

The project aim to do a detailed study on real world car-to-bicyclist accidents, using the accident database GIDAS. One of the goals is to develop a method to geometrically classify car-to-bicyclist accidents. In this way all types of accidents can be sorted into a fixed set of scenarios. For each of these scenarios a detailed statistical study can be done to get a better understanding of the car-to-bicyclist accident. Further on, logistic regression can be applied to find the most influencing risk factors for the severity of an accidents. Finally, different active safety solutions can be discussed using the risk factors as a basis.

2

Data

Accident databases are often used when trying to improve traffic safety. One of the most detailed databases of this kind is GIDAS. In this chapter GIDAS will be discussed as a base for the studies in this thesis.

2.1 GIDAS

GIDAS, short for German In-Depth Accident Study, is one of the most detailed accident databases existing today. It started as a joint project between FAT (Forschungsvereinigung Automobiltechnik) and BASt (Bundesanstalt für Straßenwesen) in July 1999 with the goal to collect at least 2000 accidents per year.[4]

Each accident studied by GIDAS contains between 500 to 3000 variables of data describing the case, including both pre-crash, in-crash and post-crash information. Some examples of information stored in the variables are:

- Accident details, such as the cause of the accident
- Dynamics, such as the initial velocities, geometrical configurations, impact positions
- Environment, such as road layout, weather, light conditions
- Participants, such as age, length, weigth
- Vehicles, such as type, mass, equipment

The accident studies and data gatherings are done within two areas in Germany, Hanover and Dresden. These areas are defined to cover both city and surrounding rural areas. In Hanover the city together with the surrounding rural area within a diameter of approximately 80 km are covered, with 1.2 million residents. The same holds for Dresden, with a diameter of 60 km covered, including 925 000 residents.[5]

2.1.1 Methology and accident investigations

For both Hanover and Dresden, GIDAS has a research team. Each of the teams consists of two technicians, a physician and a co-ordinator. The teams are also supplied with two vehicles, one for the technicians and one for the physician to accompany injured persons to the hospital.

When an accident occurs, and the local police or fire deparment have been alarmed, they in turn will immediately contact the resarach team. Thereby the research teams are able to start the investigation of an accident almost immediately after it occured.

However, whether an accident gets investigated or not depends on sveral factors. The investigations takes place each day during two six hour time intervals following a two week cycle. During the first week the investigations are carried between 12:00 a.m. to 06:00 a.m. and from 12:00 p.m. to 06:00 p.m., and during the second week through the other two time periods. The first reported accident involving at least one personal injury is investigated followed by all other subsequently reported accidents with the same criteria. In case of overlapping of accidents, the team investigates the most recent accident after they are done with their first investigation.

The investigation consists of data gathering at the site, interrogation of witnesses, data gathering on the hospital and retrospective studies. The latter type of studies varies and could be anything from post examination of the spot of the accident to gathering data from the involved vehicles at a scrap yard.[5]

2.2 GIDAS-PCM

The most important information when considering active safety systems while studying accident data are the pre-crash parameters. GIDAS contains some pre-crash parameters, however it does not include any time dependent variables, such as the velocity during the last seconds prior to collision. This kind of information requires more detailed reconstructions and further simulations, which have been done for a subset of the accidents in GIDAS. These detailed reconstructions is stored in an extension to GIDAS called the pre-crash matrix (PCM).[6]

GIDAS-PCM include information about the velocities, wheel angles, locations of the involved vehicles and driver actions such as steering and braking or accelerating at a given time point, for the last five seconds before collision. The road together with all road lines and road marks at the location are also included.[7]

GIDAS-PCM also include stationary objects considered to hinder sight during the course of the accident situation, if they were noted by the technicians on the accident scene. However no dynamical objects, such as surrounding traffic, are included, since these are hard to implement in the reconstruction models with any accuracy. This further limits what estimates and predictions are possible.

2.3 Data sets

GIDAS contains all types of traffic accidents. Each accident can be a complex process with more than two vehicles involved. In order to study the car-to-bicyclist accidents these cases have to be extracted from the database. The following properties will be used to select the car-to-bicyclist accidents:

- The accident involves a colliding car and bicycle.
- The first impact of the car is with the bicycle and the first impact of the bicycle is with the same car.
- The car is an M1-vehicle.[1]
- The bicycle is a bicycle, powered bicycle or light powered bicycle.

2.3.1 GIDAS and GIDAS-PCM sample

Data extraction was done by using Statistical Analysis System (SAS) and Structured Query Language (SQL). By combining the tables *persdat* containing general information about all persons involved in each accident, *fahrzeug* containing general information about all vehicles involved in each accident and finally *umwelt* containing information about scene of the accident, 8407 persons *traveling* on a bicycle (8288), powered bicycle (106) or light powered bicycle (13) were found.

By now considering all *bicycles* as collision opponents, data was collected for each bullet vehicle from *fahrzeug*.[2] It was found that 6524 of the bicyclists above were included in the reconstruction table, named *reko*, as a collision opponent, giving 6622 impacts since some bicyclists were hit multiple times in the same accident. These bicyclists were travelling on a total of 6469 different bicycles, which means that 55 bicyclists were passengers and thus some bicycles carried two

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[1] Vehicles used for the carriage of passengers and comprising not more than eight seats in addition to the driver's seat.[8]

[2] Bullet vehicles are vehicles having a collision with the collision opponent.

or more persons. The bicyclists hit more than once were removed leaving 6433 *bicyclists* and 6378 *bicycles*, which still gives 55 passengers.

By observing the *bicyclists* as bullet vehicles instead, 6424 (of the 6433) *bicyclists* were included in the reconstruction table as having a collision with another vehicle. This implies some inconsistency in the GIDAS tables, since 9 more bicyclists were registred as collsision opponents. Of the 9 missing cases, the case 1020367 were looked into in detail, to verify that GIDAS in fact had inconsistencies.

In total the 6424 *bicyclists* had 6424 recorded impacts with vehicles from the above table. Of these, 4871 were struck by an M1 vehcile. The car-to-bicyclist collision was the first collision for both car and bicycle in 4789 cases. Finally, from these cases 1365 were fully reconstructed in GIDAS-PCM.

2.3.2 Subsets based on injury levels

All accidents in GIDAS involve at least one injured person. It is desireable to sort the accidents depending on the severity level of the injuries. By dividing the data sample into three subsets containing the slightly, moderatly and severly injured bicyclists a more detailed analysis can be made. Studies can then be done for each subset to adress diferences between the groups.

AIS

To divide the accidents into slight, moderate and severe injuries an injury scale has to be introduced. GIDAS use AIS, which stands for the abbreviated injury scale, to classify the severity of injuries.[4] The scale goes from one to six where higher numbers means more severe injuries, the following list gives an example of a typical injury for each level:[9]

AIS1 - ‘superficial laceration’

AIS2 - ‘fractured sternum’

AIS3 - ‘open fracture of humerus’

AIS4 - ‘perforated trachea’

AIS5 - ‘ruptured liver with tissue loss’

AIS6 - ‘total severance of aorta’.

The injury scale does not include a specific level for fatals, although AIS6 and even AIS5 most often lead to fatalities. Accidents where a participant dies due to their injuries within 30 days after the collision will be considered as fatal.

From now on AIS1 injuries will be used as the slight injuries, AIS2 as moderate injuries and AIS3+F (AIS3 and higher, including fatals) as the severe injuries.

Final sample

The final sample now includes 4789 cases in GIDAS and 1365 cases in GIDAS-PCM. Of the 4789 cases in GIDAS 3713 had maximum injury level AIS1, 870 AIS2 and 206 AIS3+F. For GIDAS-PCM 994 had maximum injury level AIS1, 290 AIS2 and 81 AIS3+F. An overview of the data sets can be found in figure 2.1.

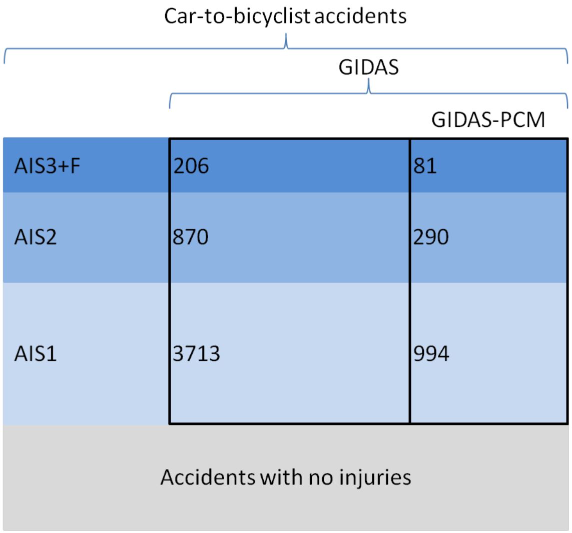


Figure 2.1: Overview of the data sets. The outer rectangle represents the unknown amount of total car-to-bicyclist accidents happening in Hanover and Dresden. The larger inner rectangle represents the 4789 cases in GIDAS. The smaller rectangle represents the 1365 (of the 4789) cases in GIDAS reconstructed in GIDAS-PCM, i.e. the GIDAS-PCM subset. Finally the three different colors represent the subsets based on injury levels.

3

Accidentology

In this chapter the car-to-bicyclist accidents from GIDAS will be analysed to understand the context in which they occur. In particular, situational parameters important for car-based active safety systems will be studied.

3.1 Accident classification method

An accident can be described by a set of variables. As mentioned in the previous chapter the number of variables GIDAS record is about 3000. The variables can also be divided into pre-crash, in-crash and post-crash parameters. The pre-crash variables describe the accidents before the actual collisions take place and contain information such as initial velocities and geometrical conditions. In-crash variables on the other hand describe the actual collision, such as impact points for vehicles and possible pedestrians or bicyclists. Finally, the post-crash variables give information about events after the collision, e.g. whether any participants had to visist a hospital etc.

Of the three types of variables the most important for active safety systems are the pre-crash variables. These either hold the same type of information the system utilise in predictions and estimates of traffic situations, or information about the typical conditions the system will have to work in. Thereby the main focus of the accidentology will be on the pre-crash variables.

The goal of the accidentology is to find common type of accident scenarios. The most important information to breakdown is the pre-crash dynamics and geometrical configuration of the involved vehicles. This information alone will give requirements and necessary properties for any proposed system, and also specify the limitations. For example, some of the AEB systems today may not activate if the car is turning.

Based on this, the study will be divided into two steps. First a geometrical classification will be done to see what types of geometrical accident scenarios are most common. Then a specific subset of environmental and descriptive variables considered essential for the development of active safety system will be studied for each of the scenarios.

3.1.1 Geometrical accident scenarios

As previously mentioned, it is desireable to group similar accidents based on their geometrical configuration and pre-crash dynamics to find common scenarios. In order to do so, a set of classes describing general geometrical scenarios have to be defined. There is no obvious way to define the classes, however they should be as few as possible while still providing sufficient information. The classes should also be defined in such a way that each accident can be assigned one class uniquely. They should also be easy to implement on different types of data sets for comparisons, in particular it should be appliable on the GIDAS database.

The information treating the pre-crash dynamics and geometrical configuration can be divided into three categories: the motion of the car, the motion of the bicycle and their relative location. For car-based active safety systems, the relevant information is the motion of the car and then the location of the bicycle together with its motion.

By only considering vehicles travelling forward there are two possibilities for the motion of the car, either it is travelling straight ahead or it is turning. The turning motion can be to the left or right, and it makes sense to distinguish between the both because of traffic rules and infrastructure. The information regarding the bicycle is more difficult to process, since the relative location together with the motion is hard to generalize. However, if the motion of the car is allready known, one can consider the travel direction of the bicycle instead to get a good approximation of the motion and location of the bicycle.

Based on these conditions the following classification procedure was defined. First the ongoing motion of the car *in* the collision is determined to be either left turn, going straight or right turn. This gives three possible outcomes with each outcome corresponding to one class. Further on, a car is considered to only have one of these motions which in turn makes the three classes disjoint. Secondly, each class is divided into four subclasses corresponding to the relative motion of the bicycle seen from the car *before* the collision. The bicycle is considered to either be going in the opposite, right, same or left direction, yielding 12 possible outcomes and therefore 12 subclasses in total. A graphical representation of all the classes can be found in figure 3.1.

In order to use the classification, the different motions of the car and directions

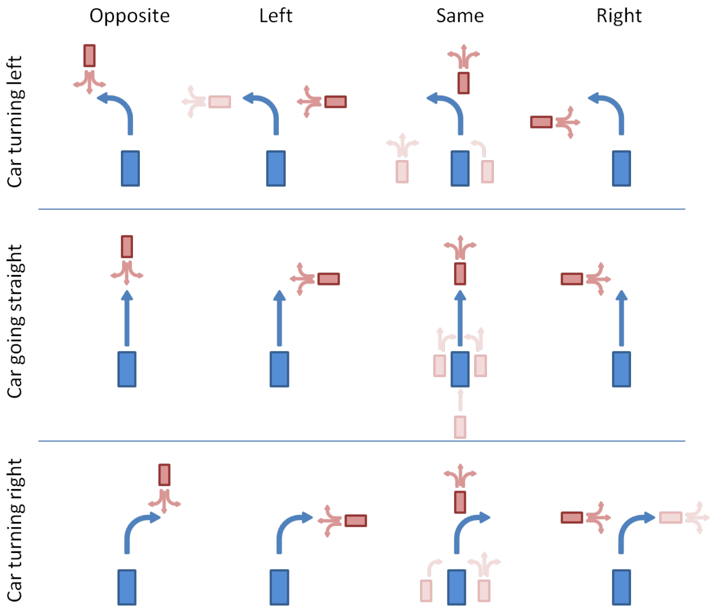


Figure 3.1: A graphical representation of the geometrical classfication. Each row corresponds to the motion of the car, and the columns correspond to the relative travel direction of the bicycle.

of the bicycle needs to be distinguishable. This needs to be further specified based on what data the classification is applied on. In GIDAS there is a pre-defined variable called UTYP, which gives each accident an accident type which in turn gives a basic description of geometrical configurations of the accident. In GIDAS-PCM however, the motions can be explicitly defined based on the reconstructed data. In this work the two methods will be compared.

Classification of accidents in GIDAS-PCM

In GIDAS-PCM the reconstructed time dependent data can be used to classify the accidents. In the first step the motion of the car in the collision, has to be determined. In order to do so a clarification has to be made regarding what is considered to be a turning motion. One efficient way of doing this is using the reconstructed wheel angles. The most simple method would be to set a treshold for the wheel angle in the collision and choose all cars with a wheel angle over this treshold to be considered turning. However, with this approach, all cases where the car is just finishing its turning motion will be regarded as car going straight.

Another solution would be to check whether the car is in an ongoing turning motion in the collision, i.e. whether the wheel angles deviate from zero.Then the turning motion can be tracked backwards to see if the wheel angle ever reaches the critical value during its turning motion.

The problem with these approaches is to find an appropriate treshold. The treshold can be tuned to give results adapted for a specific solution. However, since no specific solution is considered, a general approach has to be found.

It is desired to find all turning scenarios in intersections but to leave out avoidance manoeuvres and bends on highways with a low turning angle. Avoidance maoeuvres can be removed by giving the requirement that the turning motion should be initiated at least one second before the collision. Further, the wheel angle treshold can be chosen by looking at turning radii. In figure 3.2 the turning radius can be seen as a function of wheel angle for a car with a wheel base of two metres. A wheel angle of 3° gives a turning radius of 38 m which is equal to about the width of 10 road files. Three degrees would thus be a sufficient treshold for sorting out turning motions.

Further on the sensitivity of the treshold can be studied. This is done by defining a function to be the proportion of the data set classified as turning with respect to the treshold. The derivative of the function is then studied to see if a small change in the treshold affects the classification result. The derivative can be found in figure 3.2, which indicates that 3° is a good choice since a small change in the treshold does not affect the result of the classification.

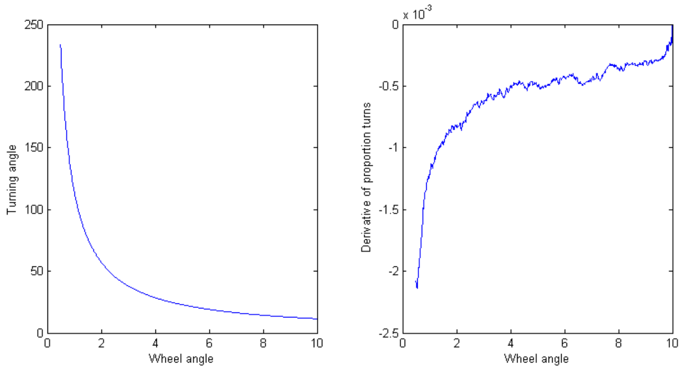


Figure 3.2

In the second step of the classification, the relative motion of the bicycle seen from the car was determined. This was done by using the angle between the longitudinals of the vehicles. Let α be this angle, then for $\alpha \leq 45°$ or $\alpha \geq 315°$ the bicycle is considered to move in the same direction, for $45° < \alpha < 135°$ the left direction, for $135° \leq \alpha \leq 225°$ the opposite direction and for $225° < \alpha < 315°$ the right direction. An illustration of this can be found in figure 3.3.

Note that the classification procedure is done in order to find common types of geometrical configurations among the accidents. There will be similar accidents

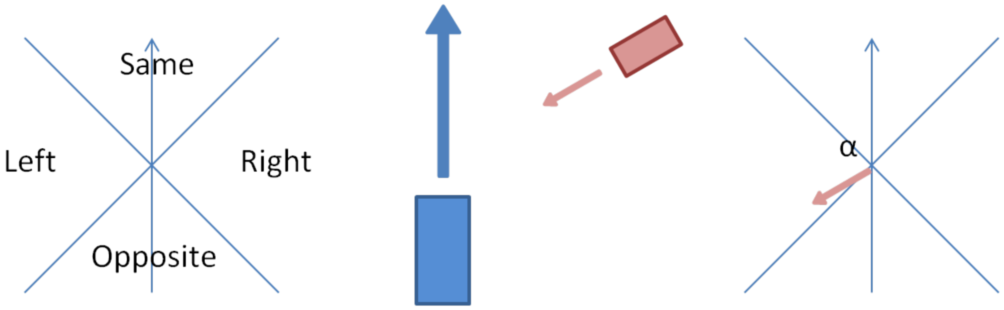


Figure 3.3: The direction of the bicycle (red) seen from the car (blue).

close to the boundary, which gets sorted into two different classes. However, the main part of the accidents in each class is clearly within the borders of the definition. Thus the final results is not greatly affected, partly what figure 3.2 shows about the motion of the car.

Classification of accidents in GIDAS

GIDAS does not contain reconstructed data to the same extent as GIDAS-PCM. Instead a variable called UTYP can be used to geometrically classify the accidents. UTYP is a three digit code giving a brief explanation of the accident, including a general description of the geometrical configuration of the vehicles in the pre-crash phase.[4] There are several hundread different codes, and each code defines a scenario by an explaining figure. The participants in each scenario are also denoted by a letter. An example of an UTYP scenario with the defining figure can be found in figure 3.4.

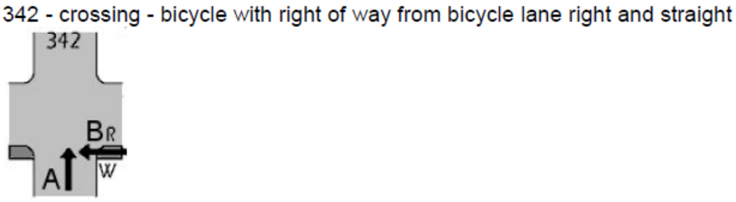


Figure 3.4: The defining figure for UTYP code 342. The two participants are denoted A and B.

It is important to note that the UTYP code considers the conflict situation that led to the accident. Thereby if several vehicles are involved in an accident, the vehicles described in the UTYP code will not necessarily be the same as the ones colliding. This may lead to confusions for the purpose of the geometrical classification. However, the effect should not be noticeable for the data sample used here, since only the first collision of each accident is used.

The classification is done by grouping accidents with UTYP codes describing similar scenarios. In table 3.1 the codes used for each class can be found. The letters denote which of the participants is the car, and is necessary to include since one UTYP code can describe two different scenarios depending on this. The classification also has to be done for accidents from 2006 and onwards since there was no way of distinguishing the participants in the UTYP-codes before that.

Class	UTYP
LO	A211, A224, B224
LL	A322, B352
LS	A223, B223, A202
LR	A302
SO	B211, A681, B681
SL	A342, B342, A321, B301, A371, B371, B302, B303, A344, B344
SS	A581, B581, A501, B501, A601, B601, B232, B202, A651, B651, A374, B374, A582, B582, A502, B502, A551, B551, A611, B611
SR	A341, B341, B321, A301, A372, B372, B322, B323, A343, B343, A352
RO	A244, B244
RL	A323
RS	A243, B243, A232
RR	A303

Table 3.1: Translation table between the most common UTYP-codes used in car-to-bicycle accidents, and the geometrical classes. The abbreviations in the leftmost column stands for the classification i.e. LO stands for car turning *left* with the bicycle travelling in the *opposite* direction. The letter before the UTYP-codes indicates which of the participants is the car in the UTYP-definitions.

3.1.2 Descriptive variables

The geometrical classification provides useful information on its own, however it also leaves out information about the environs and the scene of the accident. Thus a more in-depth study was done for each geometrical class to find common trends among the descriptive variables.

One of these variables is the road scene. Although two accidents may have the same pre-crash geometrical configuration the road scene may change the conditions for mitigation of the accident. For example an accident happening when a car is moving straight and the bicycle is crossing its path moving in the left direction does not necessary have to occur in an intersection.

Whether an accident occurs within a city or in a rural area is also of interest. This is often connected to the speed of the car due to the higher speed limits in the rural areas. The speed of the car in itself is also of great importance, as well as the speed of the bicycle, since higher impact speeds tend to cause more severe injuries.

Variables describing the vision conditions of an accident scene can also give a hint of possible active safety solutions. In particular, whether accidents tend to occur during the day or night is important. It is also relevant to keep track of rainfall or other factors prohibiting the vision for both the driver and potential sensors.

Finally, detailed information about the bicyclists was gathered, such as the age, height and gender. This in order to find whether any particular groups were overrepresented which may affect the possible countermeasures.

3.2 Geometrical classification

The results from the geometrical classification of the accidents in GIDAS-PCM can be found in figure 3.5. The scenarios where the car is moving straight forward are the most common for all injury levels. However, they get even more common with higher injury levels. The reason for this observation is that higher impact speeds in general result in more severe injuries, and turning cars tend to have lower speeds than cars travelling straight forward. This will be further investigated in the descriptive statstics study, see section 3.3.

The crossing scenarios, where the car is moving straight forward and the bicycle is moving either to the left or right seen from the car, are extra common. For severe injuries they represent more than half of all accidents. The two longitudinal straight cases also make up for a large part of the accidents.

3.2.1 Classification using UTYP

The UTYP approach for the classification was compared to the classification by reconstructed data. All accidents from 2006 and onwards in GIDAS-PCM were used to see if the results agreed, which can be seen in figure 3.6. Although the relative size of the largest groups seem to agree there is one main difference. Cases where the car is turning right are considerable less frequent, in particular when the bicycle is moving in the left direction.

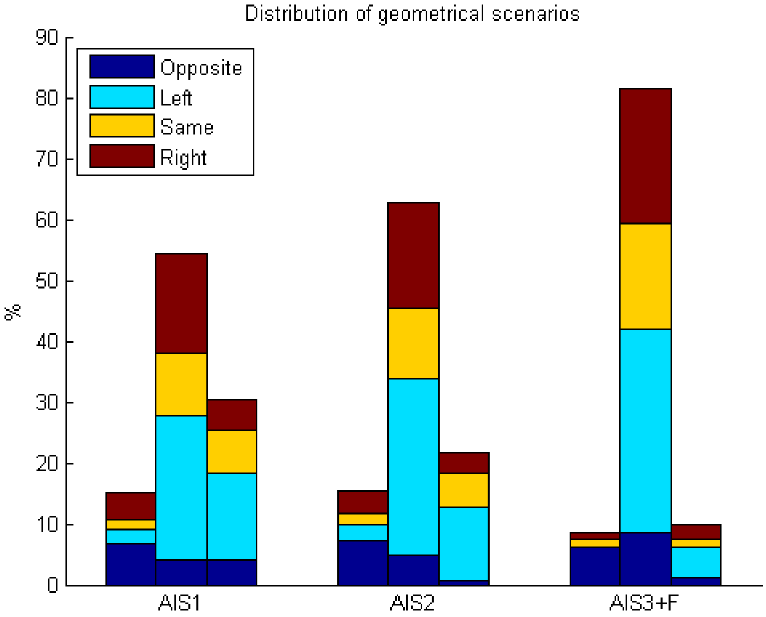


Figure 3.5: Geometrical classification for the GIDAS-PCM subsets of accidents. The three collection of bars each correspond to one injury level. Each collection contain three bars, the left bar corresponding to the car turning left, the middle bar corresponding to the car moving straight forward and the right bar corresponding to the car turning right. Each collection of bars sums up to 100%, giving a relative measure of the representativeness of the different scenarios between the diferent subsets.

To find the diferences a table was made displaying how each case was classified by both methods, which can be found in figure 3.7. The table showed the same result as figure 3.6, that there was a large group of accidents classified as the car turning right with the bicycle moving in the left direction when using the reconstructed data. Most of these accidents however, were classified as the car moving straight forward when using UTYP. By specifically looking into these turning scenarios it was found that only about 5% of the accidents used an appropriate UTYP code. Further on, 80% of these accidents used UTYP code 342 (see figure 3.4), which were used for cars moving straight with bicycle moving in the left direction. The common factor for these accidents were that they all had the bicycle travelling on a bicycle lane before the collision. This fact seemed to override the geometrical configuration, and since there were no code for the car turning right and the bicycle travelling in the left direction on a bicycle lane, the UTYP code 342 was used instead.

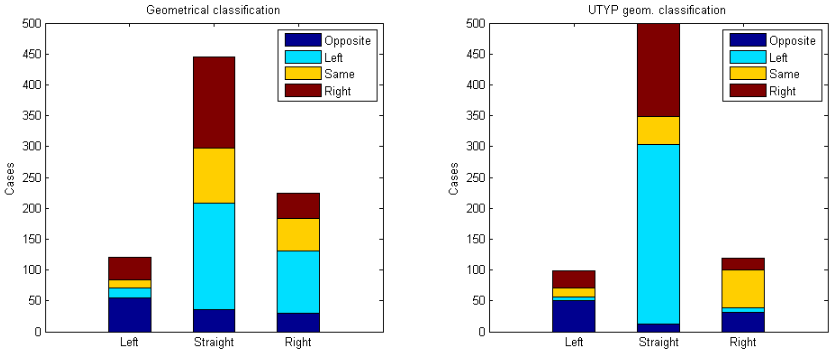
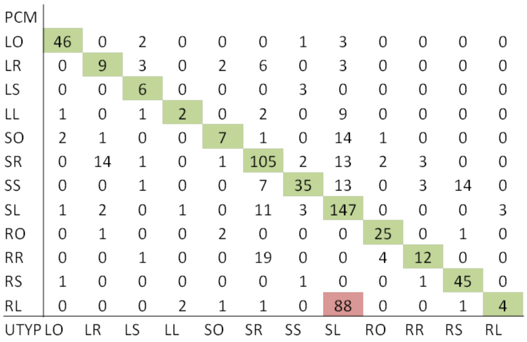


Figure 3.6: Geometrical classification for the 790 GIDAS-PCM cases from 2006 and onwards using reconstructed data to the left and UTYP to the right.



PCM												
LO	46	0	2	0	0	0	1	3	0	0	0	0
LR	0	9	3	0	2	6	0	3	0	0	0	0
LS	0	0	6	0	0	0	3	0	0	0	0	0
LL	1	0	1	2	0	2	0	9	0	0	0	0
SO	2	1	0	0	7	1	0	14	1	0	0	0
SR	0	14	1	0	1	105	2	13	2	3	0	0
SS	0	0	1	0	0	7	35	13	0	3	14	0
SL	1	2	0	1	0	11	3	147	0	0	0	3
RO	0	1	0	0	2	0	0	0	25	0	1	0
RR	0	0	1	0	0	19	0	0	4	12	0	0
RS	1	0	0	0	0	0	1	0	0	1	45	0
RL	0	0	0	2	1	1	0	88	0	0	1	4
UTYP	LO	LR	LS	LL	SO	SR	SS	SL	RO	RR	RS	RL

Figure 3.7: Table illustrating the classification of each accidents by using both the reconstructed data from PCM and the UTYP code.

The remaining 15% of the cases seemed to be directly coded in the wrong way. For exampl, 3% used UTYP code 341 which is similar to 342 but instead the bicycle is traveling on the opposite side of the car in the right direction. It may also be that there in fact was another bicycle from the left travelling to the right, and that the technician judged that it was that bicyclist who caused the accident. Although the car in the end collided with another bicyclist. However, the turning motion of the car was still not included.

The conclusion was that GIDAS-PCM provided a more accurate result based on what is needed for this analysis. Thereby GIDAS-PCM will be used for the rest of the studies.

3.3 Descriptive statistics

As previously mentioned the geometrical classification does not provide any information regarding the environs and scene of the accident. Instead a set of complementing descriptive variables were studied for the most common geometric scenarios.

The first two variables studied were the road scene and type of area for the accidents, which both can be found in figure 3.8. The distributions between the different road scenes and type of areas is similar between the different groups, except for the longitudinal cases which have less accidents in intersections.

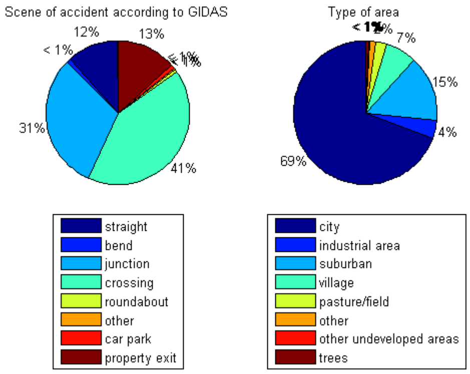


Figure 3.8

Further on, the speed of the car and bicycle was investigated for each geometrical class, the result can be seen in figure 3.9. The assumption of higher speeds in the straight cases seem to be correct. There is also, relatively, more AIS2 and AIS3+F cases to the right in the plots which indicates that the other assumption of higher speeds giving more severe injuries, is true. The weakness of the reconstruction method for the speed of the bicyclists also becomes appearent. In most of the accidents the reconstruction method is able to estimate the speed of the bicycle with an accuracy of 5 km/h explaining the pattern of the plot.

Variables affecting vision were also studied. Most of all car-to-bicyclist accidents occur during day time, as can be seen in figure 3.10. There were no larger variations between the different classes and injury levels. However, this information only considers the absolute number of accidents and does not tell anything about whether there is a larger risk of accidents to occur during the day or night. Further on, most accidents also occur when there is no rainfall. These results are reasonable, since there tend to be more bicyclists during the day and in good weather conditions.

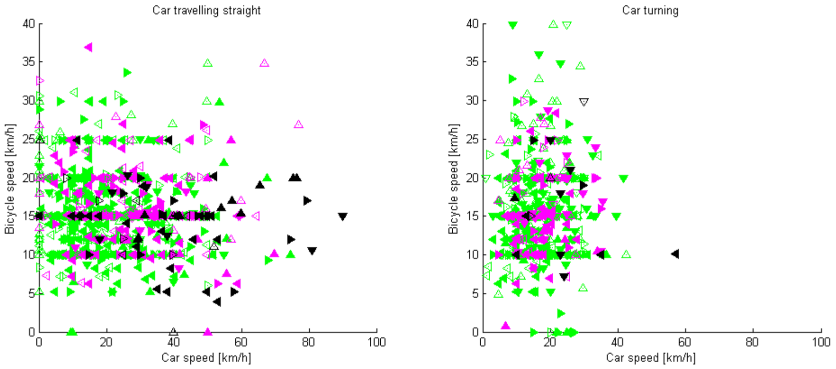


Figure 3.9: Scatter plot of the speed of the car and the bicycle. The triangle points in the travel direction of the bicycle. A filled triangle corresponds to an accident where the bicycle hits the front of the car, where an empty triangle corresponds to all other types of collision. The green, magenta and black colors corresponds to an AIS1, AIS2 or AIS3+F injury respectively. The accidents were ploted in an increasing severity order, in order to make the more severe injuries visible.

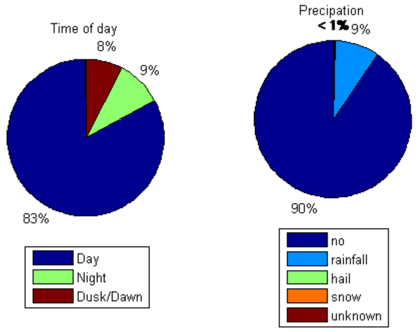


Figure 3.10

Finally, the height, age and gender of the bicyclist were analysed. There were no large variations in age distributions between the different geometrical classes, however the age distribution differs between the injury levels, which can be seen in figure 3.11. The higher injury levels tend to increase the average age of the bicyclist, i.e. older people tend to get more severe injuries if they are involved in a car-to-bicyclist accident. Further on the height of the bicyclist is weakly connected to the age, and no larger variations were found between the groups. In other words, there was no particular group where for example children were overrepresented. The same holds for the gender which only have a slight difference between injury levels.

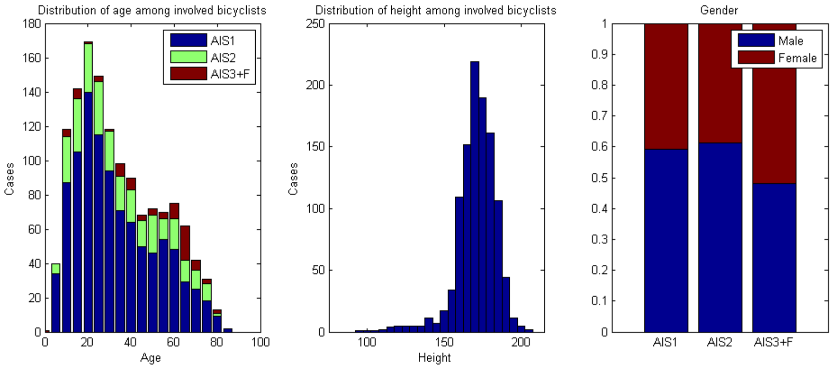


Figure 3.11

3.4 Summary of representative scenarios

From the geometrical classification it was found that most car-to-bicyclist accidents occur when the car is driving straight forward. This observation is even more appearent for accidents with higher injury levels. Of the straight scenarios the two cases where the bicycle is crossing the travel direction of the car were the most common. Further on most of these accidents occur in intersections.

These results suggest that an effective safety system has to at least be able to adress the crossing scenarios, but also the longitudinal scenarios. The system also has to be able to operate in intersections. Finally, most accidents tend to occur during day time with no rainfall, giving good conditions for vision sensors.

4

Risk analysis

In this chapter risk curves will be developed to understand the most influencing parameters for the severity of car-to-bicycle accidents.

4.1 Statistical methods

There are several ways to interpret the concept of risk into traffic safety. It can be used to estimate the probability of an accident to occur under some specific conditions or to predict the injury severity of an accident given a set of conditions. The latter type of study is of intereset in this work since it can be used to evaluate the benefit of an acitve safety system.

The aim of the risk analysis is to find the probability of a car-to-bicyclist accident to result in a certain injury level *given* that an accident resulting in an injury occurs. Injury levels that will be used are AIS3+F and fatalities alone.

4.1.1 Logistic regression

As mentioned above it is desired to predict whether an accident will result in a certain injury level given a set of descriptive variables. The injury level can be seen as a binary response, either the accident result in the requested injury level or not. It is therefore suitable to use logistic regression to estimate the probabilities using the descriptive variables as independent variables or predictors. The probability of an accident resulting in a certain injury level is thereby assumed to be on the form of the logistic function,

$$\mathrm{P}(\mathbf{x}) = \frac{1}{1 + e^{-(\beta_0 + \boldsymbol{\beta} \cdot \mathbf{x})}}. \tag{4.1}$$

To find which descriptive variables to include in $\mathbf{x}$ multiple regressions will be performed on diffrent combinations of variables suspected to have a great impact on the probability. The best model will then be selected based on AIC (Akaike information criterion), AUROC (Area Under Receiver Operation Characteristic) and visual tools such as leverage.

Akaike information criterion

AIC gives a relative measure of quality between models and is defined as,

$$\mathrm{AIC} = 2k - 2\ln L, \tag{4.2}$$

where k is the number of parameters in the model and L is the maximum of the likelihood of the model. It utilises how close a models fitted values relative to the true expected values are (by maximum likelihood), and penalises the model for having many parameters. The prefered model, when selecting from a set of candidates, based on AIC is thus the one with lowest value. A simple model will always be farther away from the true model compared to a more complex model, e.g. a model containing more variables. However, for some samples the simple model may provide better estimates of the true expected values. [10]

Reciver operating characteristics

AIC gives a good relative measure between the models, however there is also a need for an absolute measure. The ROC curve is a good compliment to AIC and provides a measure of the performance for a model. A ROC curve is produced by ploting the true positive rate (sensitivity) against the false positive rate (1-specificity) of the model, in the following way. Let all cases with a probability higher then a cutoff π be classified as positive. For example, in the AIS3+F model this would mean that each accident with a probability, predicted by the model, to be higher than π is assumed to result in a AIS3+F injury. Then plot the sensitivity against one minus the specificity, i.e. the rate of all cases with a true positive respone against the cases with false positive repsonse, for all possible values of $\pi \in [0, 1]$.[10]

As $\pi \to 0$ almost all cases will be predicted as positive and so the sensitivity will go towards 1 and the specificity will go towards 0, giving the cordinate (1, 1) for the ROC curve. On the other hand if $\pi \to 1$ almost all cases will be predicted as negative, giving 0 in sensitivity and 1 in specificity. This results in the ROC curve, usually, having a concave shape with connecting points in (0, 0) and (1, 1). A perfect model would give perfect sensitivity for all levels of specificity, and so the perfect ROC curve would be a line from (0, 1) to (1, 1). In the same sense, a random model would just give a line from (0,0) to (1,1).

To give a numeric value to this measure of performance, the ROC curve can be integrated, to get the area under the curve (AUROC). A perfect model would thus give an AUROC value of 1 whereas a completly random model would give an AUROC value of 0.5.

4.1.2 Implementation

The data set used for this study will be all accidents in GIDAS-PCM which gives a sample size of 1365 accidents. The AIS3+F subset consists of 81 accidents and of these 11 are fatalities. The small amount of fatalities restrict the possibilty of any accuracy in the fatality risk model and thus the AIS3+F model will be studied in more detail instead.

Since the risk model will be based on the GIDAS-PCM data it will give the probability of an accident to result in a certain injury level *given* that an accident occurs with at least one injury. This is because of the data gathering procedure of the GIDAS database, see section 2.1.1.

What variables to include in the regression model can partially be determined from the accidentology. In the accidentology study it was found that the speed of the car may have great impact on the outcome of high injury levels, as seen in figure 3.9. The car speed, v_{car}, will thus be used as a base in the regression model, where more variables can be added. Some other variables from the accidentology that may be of interest are properties of the participants and details of the collision. The inclusion of parameters directly affecting the probability of a collision to occur are unnecessary, since the estimation for the injury levels are based on the conditions that an accident occurs.

The numerical calculations for the logistic regression will be done with Matlab Statistical Toolbox, in particular the `GeneralizedLinearModel` object will be used.[11]

4.2 Risk model

The probability of an accident to result in a fatality and the probability of an accident to result in an AIS3+F injury, based on the impact speed of the car, can be found in figure 4.1. The fatality model shows good performance based on the ROC curve with an AUROC value of 0.95, indicating an almost perfect model. However, this is mainly due to the low number of collisions result in fatalities giving an overfitted model. The model for AIS3+F show less performance based on the ROC curve, indicating that more information is needed to do accurate predictions.

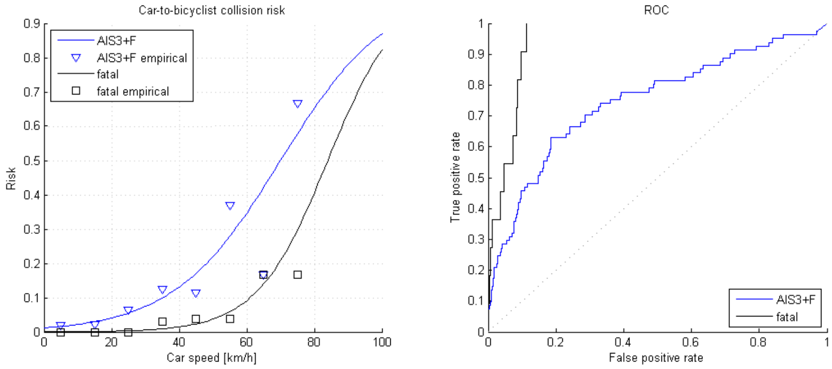


Figure 4.1: The probability of a car-to-bicycle collision to result in a AIS3+F injury shown in blue, and fatality shown in black. The empirical values, i.e. the proportion of positives in each category are also ploted. The probability increases very rapidly for both curves for car speeds over 40 km/h.

Variables	AIC	AUROC
v_{car}	539.8	0.749
$v_{\text{car}} + b_{\text{age}}$	493.8	0.809
$v_{\text{car}} + b_{\text{age}} + b_{\text{gender}}$	491.6	0.811
$v_{\text{car}} + b_{\text{age}} + v_{\text{bike}} \cos \phi_{\text{rel}}$	490.1	0.815

Table 4.1: AIC and AUROC for the different AIS3+F models. ϕ_{rel} denotes the relative angle between the directions of the vehicles.

4.2.1 AIS3+F

To get better performance of the AIS3+F risk model, additional variables were added to the model. The age of the bicyclist, b_{age}, was the variable next, after the car speed, suspected to have an impact on the injury outcome of an accident. By adding the age of the bicyclist to the model the AIC decreased from 539.8 to 493.8. The AUROC value also increased from 0.749 to 0.809, which can be seen in table 4.1.

To further increase the performance two additional variables from the accidentology study were tried in combination with the speed of the car and the age of the bicyclist. The gender of the bicyclist, b_{gender}, seem to give a small impact on the risk from the accidentology. However, the effects showed to be too small to give any notably effects, lowering the AIC from 493.8 to 491.6 and increasing the

AUROC from 0.809 to 0.811. Further on, the relative speed of the bicycle in the direction of the car either increase or decrease the relative impact speed between the vehicles. Thereby it is suspected to also affect the injury outcome, which also can be seen in table 4.1. It gives a slightly higher increase in AUROC and decrease in AIC than adding the gender. This model was chosen to be further analysed.

Collision dynamics

Although the speeds of the vehicles in the impact tell much about the collision dynamics it leaves out some information. Since the AIS3+F model still seemed to lack in performance, it was suspected that the severity of an accident also may depend on more detailed collision dynamics. Several variables were tested with the model including impact points on the vehicles, geometrical configuration in collision, if and where the bicyclist hit the car and the kinematics of the bicyclist in the collision. The kinematics of the bicyclist was the only variable affecting the result.

The kinematics of the bicyclist was simplified to a set of dummy variables describing whether the bicyclist was scooped up by the car, had an impact with a directional change or was overrun by the car. The only property of significance was whether the bicyclist was scooped up by the car. However this information turned out to be strongly collinear with speed of the car and did not provide any benefit to the model.

Model fit

To get accurate predictions for the risk of a car-to-bicyclist accident to result in severe injuries seem to require a more detailed model, based on ROC. However, the model containing the speed of the car, age of the bicyclist and relative speed of the bicycle in the direction of the car, was chosen to be used as a sufficient approximation. The estimated coefficients for the variables can be found in table 4.2. The *t* statistic for a test that the coefficient is zero is also done for each variable.

Est. Coeff.	Estimate	SE	*t* stat.	p-value
Intercept	-6.40	0.439	-14.6	$3 \cdot 10^{-48}$
car speed	0.0698	0.00795	8.78	$2 \cdot 10^{-18}$
age	0.0416	0.00624	6.67	$3 \cdot 10^{-11}$
rel. bike speed	0.0298	0.0125	2.37	0.0176

Table 4.2

The leverage of each case was also studied, and can be found in figure 4.2.[1] The two cases with the highest leverage were looked into in detail. One of the accidents was an AIS3+F (fatal) case where the bicyclist was of age 13, the other was an AIS3+F case where the bicyclist was 16 years of age. Temporarily removing one of these cases at a time did not give any deviation larger than the standard error for any of the coefficients.

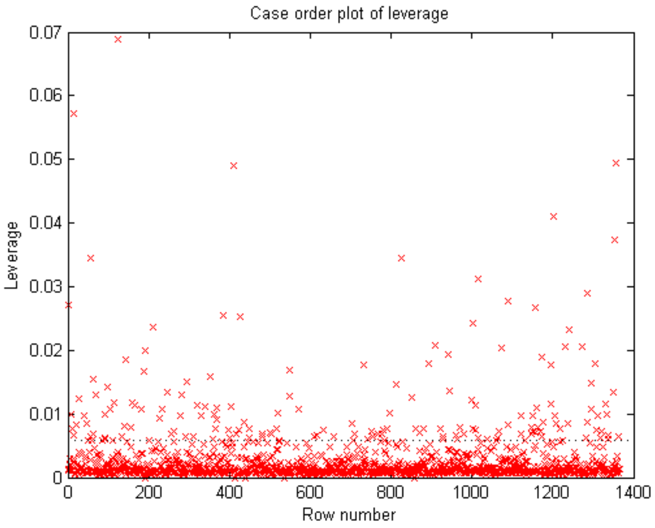


Figure 4.2

This risk model gives a sufficient approximation to discuss possible solutions. However, it is still quite far away from the perfect model based on ROC. It is important to note that it will produce false positives and, again, is treated as an approximation. The relative speed between the vehicles is also something typical for an active safety system to handle. To reduce a high impact speed of the car drastically lowers the risk of high injury levels. Although in the future a more accurate model may be necessary to evaluate advanced systems.

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[1] The leverage describes how much an individual observation changes the model (how it affects the hat matrix). For details see [10].

5

Solutions

In this chapter active safety solutions will be discussed for car-to-bicyclist accidents.

5.1 Active safety systems and sensor design

There are many types of active safety systems, commonly they use sensors to estimate surrounding traffic and environs. If a riskfull situation develops the system may take actions to mitigate or prevent an accident. Therefore, in order to estimate the benefit of these systems, a study regarding the sensors is necessary.

Each accident will be simulated with a hypothetical sensor mounted on the car, to see if the bicycle is visible. The bicycle is considered visible if it is within the field of view of the sensor and if it is not covered by an obstruction. The coverage of the sensor is then defined as the proportion of all bicyclists, in the data set, visible with respect to the field of view of the sensor and time to collision.

5.1.1 Matlab implementation

To study the coverage Matlab will be used. For each accident a sensor will be placed in the middle of the car with a variable field of view. By tracking the relative position of all bicyclists from the car the relative angle between the car and each bicycle can be calculated. The angle is calculated from the sensor to the middle point of the bicycle, and so a bicycle is considered visible if its middle point is visible. For the middle point to be visible the relative angle has to be less than the field of view with no obstruction in the way.

5.1.2 Coverage

The coverage was studied for three groups of similar accidents. First the two lateral crossing scenarios were grouped up, then the two longitudinal scenarios were grouped up and finally all turning scenarios were analysed as one group. In figure 5.1 the relative position of the bicyclists were ploted two seconds prior to collision for each group of accidents. For the crossing scenarios a clear pattern was seen with the bicyclists located to the left and right in front of the car. The higher injury levels were also more common the further the bicyclists are from the car, indicating higher relative speed, which agreed with the risk model. Higher car speeds also gave a lower angle between the vehicles, as long as the speed of the bicycles are about the same. Thus the more severe accidents tended to be centered in the plot while the less severe accidents were more scattered.

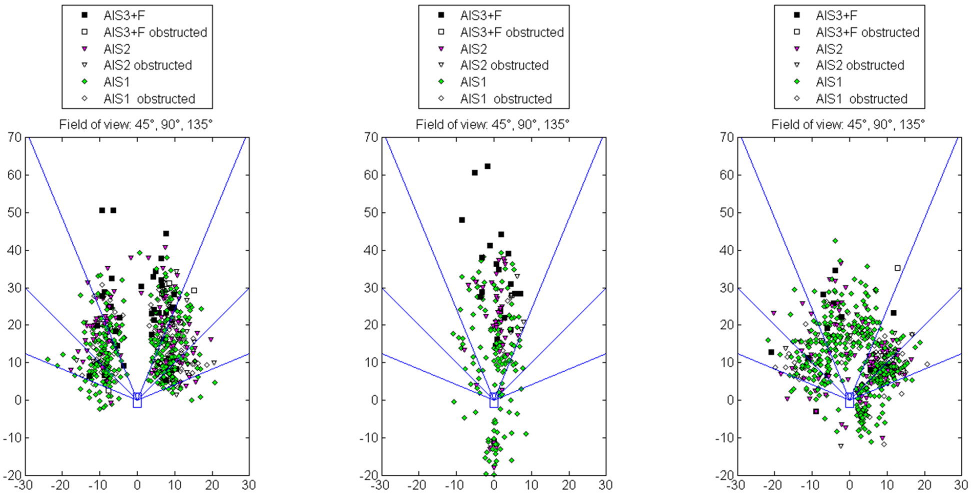

Figure 5.1: The relative position of all bicycles, two seconds prior to collision. In the left plot the crossing scenarios are ploted, in the middle the longitudinal and to the right the turning scenarios.

The longitudinal scenarios have the bicycles travelling either in the same or opposite direction of the car. Thus this group of accidents required less field of view to achieve the same results as for the lateral scenarios, if only frontal accidents are considered. However, in plot 5.1 all accidents were ploted, including the bicyclists runing into the car from behind. The same pattern for injury levels was also found for the longitudinal scenarios, where more severe injuries are more common the farther away the bicyclists were from the car.

Finally, the turning scenarios were considered. These accidents showed to be far more difficult to adress with reasonable field of views. The bicycles were almost evenly distributed around the car, as seen in 5.1. The results from the classification also became evident, where right turn scenarios often were combined with a bicycle moving in the left or same directions, whereas the right turning cars often were combined with a bicycle moving in the right or opposite direction (see figure 3.5).

The cumulative distribution function of the coverage with respect to the field of view was also ploted for each group and can be found in figure 5.2. This plot showed that less than 50° field of view was required to cover at least 50% of the severe accidents, but to cover 90% more than 100° was required. Further on, the longitudinal scenarios, as expected, showed less requirements (if only frontal accidents were considered). Finally the turning scenarios showed to require very high field of views.

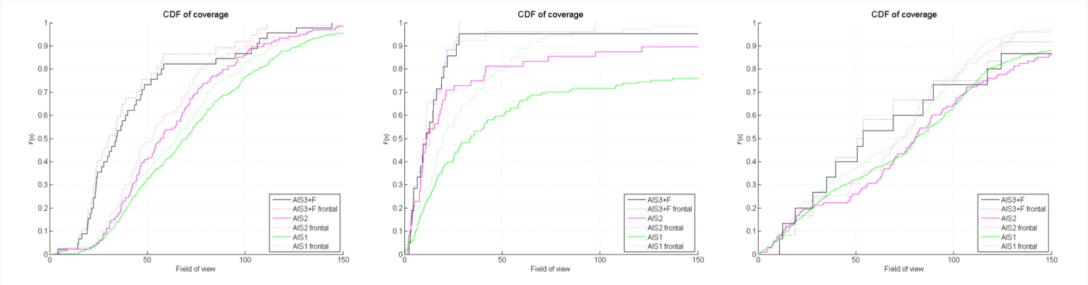

Figure 5.2: The cummulative distribution of the coverage with respect to field of view. In the left plot the CDF for the crossing scenarios are ploted, in the middle the longitudinal and to the right the turning scenarios.

5.2 Autonomous emergency braking

The coverage study showed that a sensor with at field of view of about 50° captures a considerable amount of severe accidents, and thus active safety may be possible to apply. The current state of the art soultion for active safety is autonomous emergency braking. AEB can be implemented in many different ways. Some systems may assist the driver in critical situations while other systems may perform full brakes without any interaction from the driver. Common for the systems is the use of sensors to estimate traffic situations and automatically brake if necessary.

To analyse the usability and effectiveness of AEB for car-to-bicyclist accidents a simplified model will be considered. Each accident will be simulated with the inclusion of a hypothetical AEB system in the car. To specify the AEB system five variables will be used: the field of view of the sensor ϕ_{FoV}, a maximum brake acceleration a_{max}, a trigger width i.e. a maximum lateral distance that the bicyclist is allowed to have $d_{\max}$ (from the center of the car), a maximum predicted time to collision t_{max} and a ramp up time for the brake τ. Further on the AEB system will trigger if the following conditions are fulfilled:

- The bicycle is within the field of view, and visible i.e. not obstructed.
- The bicycle has been visible for three consequtive frames.
- The car is predicted to collide with the bicyclist.
- The predicted time to collision is less than the allowed t_{max}.
- The latteral distance to the bicycle is less than the allowed value d_{max}.

If the AEB trigger the car continue in the direction it is currently travelling in, calculating a new impact speed, v'_{car}, or whether the car fully avoids the collision. The new impact speed (or miss) can then be used to estimate the effectiveness of the AEB system by implementing the risk model from chapter 4 through equation (5.1).

$$E = 1 - \frac{\sum_i \mathrm{P}({}^i v'_{\text{car}}, {}^i b_{\text{age}}, {}^i v_{\text{bike}} \cdot \cos({}^i \phi_{\text{rel}}))}{\sum_i \mathrm{P}({}^i v_{\text{car}}, {}^i b_{\text{age}}, {}^i v_{\text{bike}} \cdot \cos({}^i \phi_{\text{rel}}))} \tag{5.1}$$

5.2.1 Effectiveness

The effectiveness of an AEB system was tested for several different combinations of variables. The results can be seen in table 5.1. Overall the results were very sensitive to the specifications and thus the effectiveness of AEB is fully dependent on the system. However, even for low requirements AEB still had a considerable potential to mitigate car-to-bicyclist accidents.

Notably the effectiveness of the AEB system seem to be highly dependent on the maximum lateral trigger width d and the maximum braking acceleration. The lateral distance gives a large effect due to the high amount of crossing scenarios.

ϕ_{FoV}	a_{max}	d_{max}	t_{max}	τ	Eff.
45°	1g	5 m	1 s	0.1 s	33.7%
90°	1g	5 m	1 s	0.1 s	37.8%
45°	1g	7 m	1 s	0.1 s	53.2%
45°	0.5g	5 m	1 s	0.1 s	20.5%

Table 5.1

It is also worth noting that this approach gives the theoretical maximum potential of the AEB since there are several limitations of the model. The detection algorithms are considered to be ideal and no vision conditions are regarded, such as weather and whether it is day or night. However, as seen in the accidentology the effect of vision should not be large due to the fact that most car-to-bicyclist accidents occur during good conditions for vision sensors. Further on most car-to-bicyclist accidents occur in intersections, according to the accidentology study. In real life, inteserctions can be a great challenge for AEB due to traffic, which is not considered here.

Finally the greatest limitations are probably false positives and near misses which may bring negative consequences to the equation. Since the accident data only contains accidents with injuries the study only predict what is possible to mitigate. However, there may be a large number of accidents with no injuries or even normal traffic situations where this type of system may damage more than help.

5.3 Other solutions

Although AEB has a great potential to mitigate accidents, there are some challenges. The fact that most bicycle accidents occur in intersections has to be adressed. Intersections mainly brings two challenges, surrounding traffic and large lateral distances. The large lateral distances often induce requirements on large field of views.

To solve the problem with surrounding traffic an intersection assistant could be used instead of AEB. The intersection assistant could warn the driver if riskfull situations develop and then the driver may choose to brake. Due to the fact that the driver takes the final decision also enables the system to track riskfull objects such as bicyclists further away.

The lateral distances and field of views are more of a fundamental problem. Sensors will become better with time, but the lateral distance will remain the same. One solution to the problem could be to introduce new designs of intersections. The risk of severe injuries seem to greatly diminish with speeds lower than 40 km/h, which could be used to lower speed limits in particularly exposed intersections.

6

Conclusion

In this chapter a brief summary of the results will be given. Then a discussion will be presented together with directions for further work.

6.1 Summary

The accidentology gave an understanding of where and under what conditions car-to-bicycle accidents occurs. Most of the severe accidents seem to occur in intersection with a crossing scenario. Other notable scenarios are the two longitudinal which also are common for the severe accidents. Further on most of the accidents occur during good conditions for sensors, which is a requirement for active safety to work.

A risk curve was also developed for the probability of a car-to-bicycle accident to result in severe injuries. The most influencing variable was the speed of the car, but the age of the bicyclist and the relative speed of the bicycle was also important.

Finally active safety solutions were discussed. It was shown that car-to-bicyclist accidents often require wide field of views of the sensors to be applicable. The effectiveness of a simplified AEB system was also calculated which showed high potential for the mitigation of car-to-bicyclist accidents.

6.2 Discussion

Geometrical classification

The classification method used in the accidentology study for GIDAS-PCM showed clear trends for the most common scenarios. The method was quite stable with repsect to the treshold for the turning motion. However, there were still some accidents close to the boundary between the classes. Depending on what is sought after this may affect the results. Two groups particularly affected were the cases where the bicycle is moving in the opposite direction of the car and the car is either going straight forward or turning to the left. If these groups are of extra interest a slightly tuned version of the classification method could be benefitial. In figure 6.1 an example of two similar accidents classified as car going straight respectively car turning to the left with the bicycle moving in the opposite direction can be seen.

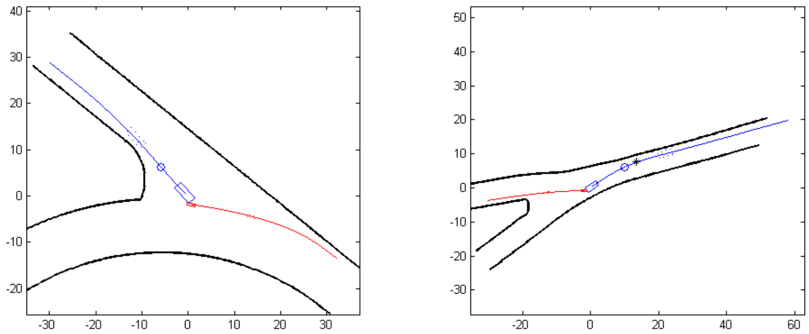

Figure 6.1: Comparison of two similar scenarios, the car is classified as going straight (to the left) and as turning (to the right). Although the cases are similar it still makes sense to classify the left as car travelling straight forward.

Although the method had some weaknesses it still provided more detailed information then by using the precoded UTYP variable. This is based on that the GIDAS-PCM reconstructions do not contain the same type of errors the UTYP codes has for some accidents.

Risk curve and effectiveness

The risk curve derived in the risk analysis could be used as a good approximation for calculating the effectiveness of AEB and discuss other solutions. However, it could still be further improved. The AUROC value of 0.815 gives a hint that more information is needed to give better performance.

The effectiveness study of the AEB system was also simplified. Although it showed good potential for car-to-bicyclist accident mitigation, the exact benefit was very sensitive to the specifications of the system. In order to get a better estimate more details could be used in the simulations. False positives and drawbacks of the system also need to be adressed. This could be done by introducting simulated traffic into more advanced simulation models. However this is not possible by only using GIDAS, since it is an accident database and only contains accidents and no data of near misses or ordinary traffic.

It is also likely that it will be hard to predict accidents with at very high probability, and so an automatic braking system may brake far more times than actually avoiding severe accidents. Thus, even rare side effects, could potentially be important if one wish to find rational design parameters for such a system. To study frequencies of side effects Field Operational Studies (FOT) are necessary to get data of accident scenarios that did not result in a collision, near misses. A similar study could then be done for this data to find the impact of the side effects, to further improve the effectiveness.

6.3 Further work

Next follow some suggestions for further work in the area:

- A more advanced risk model could be developed. This would give several benefits, such as better estimates of the effectiveness of different countermeasures. It could also be used to invent new solutions if new influencial parameters are found, not adressed by the current systems.
- Simulation methods for car and bicycle traffic could be developed. This would also give a better tool for evaluations of active safety systems.

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