Potential and Systematisation of Video-based Analysis of Bicycle Conflicts

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Abstract

Road accidents involving bicycles are becoming increasingly common in urban areas. To improve accident prevention, proactive road safety instruments (i.e., conflict analysis) are a promising supplement to the existing reactive road safety instruments. However, current research does not sufficiently account for the particularities (underestimated injury severity based on weight, speed, and collision angle) of road conflicts involving cyclists in video-based conflict analyses. To further the research on proactive safety instruments, this work developed a systematisation of existing methods using video-based conflict analysis. The recordings took place at a critical traffic node in Zurich and the resulting video data was evaluated. Conflict attributes (post-encroachment-time and time-to-collision) were calculated from the extracted trajectories. An adjusted severity formula was developed to identify and weight the potentially most relevant conflicts. The conflicts were thus analysed according to traffic mode, type of conflict, and expected collision severity, generating an analysis of conflict events at critical traffic nodes that considers the particularities of cyclists. The expected conflict severities were shown to be highest for cyclists and other vulnerable road users. These results provide an improved understanding of the conflicts and safety, supporting a more proactive approach to increasing road safety. Although the developed systematisation offers an improvement to the state-of-the-art, the collected video data has deficits. The trajectories extracted by the video remain imprecise and often cannot distinguish between the different road users. Based on this, the generation of trajectories should be further developed, and the current results of a conflict analysis should be interpreted with caution. As this work is a new attempt at an expected severity-based conflict analysis, the methodology should be further evaluated and verified at other urban traffic nodes.

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1 Introduction

In Switzerland, the number of accidents involving cyclists is stagnating while accidents involving e-bike riders specifically are increasing. In 2022, 1,371 cyclists were seriously injured or killed. The Swiss Council for Accident Prevention (BFU) assumes that the number of unreported cases of injured cyclists is much higher (Hertach et al., 2023). Accidents involving cyclists more often occur in urban areas with many nodes and a high mix of different road users (Hertach et al., 2023). Road safety professionals implement road safety measures to prevent accidents and resolve traffic conflicts.

To achieve the international goals of traffic safety, such as Vision Zero[1], new approaches to a proactive traffic safety policy are required. Since reactive safety measures are only implemented after accidents occur, proactive safety measures have the potential to be more effective in achieving the Vision Zero goal of no one being killed or seriously injured in road traffic. Road safety measures can be proactive when based on 1) traffic observations and identified conflict situations ("near misses") or 2) identified infrastructure deficits. This allows for the identification and implementation of targeted measures before these conflict situations lead to accidents and injuries. Video-based conflict analysis has the advantage of observing longer time periods and being more objective than conflict analysis based on manual observations (Eberling et al., 2022).

Most video-based conflict analyses work with road user trajectories. Based on user trajectories through the road space, user speeds and established surrogate safety measures (SSMs) can be calculated. SSMs are used to express the proximity of a potential collision by indicating the available time (in seconds) before a collision would occur if road users remained on their current trajectory without braking. Other SSMs estimate the severity of a potential collision from road users' relative speeds. However, these SSMs have not been combined in practice in a way to express both the proximity and severity of a potential collision (Polders and Brijs, 2018; Laureshyn et al, 2016).

The objective of this study is to contribute to the overarching objective of preventing accidents. For this purpose, a novel and practical approach to systematise existing video-based conflict analysis methods is proposed. Through a field experiment, a standardised method for video-based conflict analyses was developed. Conflict situations were systematically identified and differentiated based on traffic mode, type of conflict, and expected severity (i.e., considering both the probability and severity of a collision). The potential of this methodology for

[1] Vision Zero is a traffic safety policy established in Sweden with the goal that "no one will be killed or seriously injured within the road transport system" (Johansson, 2009).

improving road safety in Switzerland, with a focus on vulnerable road users such as cyclists, was assessed in this study through a comparison of recorded accidents and conflict-based expected collision severity.

The remainder of this paper contains a review of the literature on SSMs and video-based conflict analyses; a description of the methods used for processing the trajectories; the presentation of the results of the proposed method; a discussion of these results; and a conclusion.

2 Literature review

2.1 Surrogate safety measures

Practice and literature have established SSMs that objectively assess road safety. These indicators rely on creating reliable road user trajectories from video recordings. The following list presents the most relevant SSMs for this study.

- Time-to-Collision (TTC): This value describes the time until two road users collide, assuming they maintain their current direction and speed. The calculation is based on a predicted trajectory up to the point of collision. A TTC value of zero indicates a collision (Laureshyn et al, 2016).
- Post-Encroachment-Time (PET): This value describes the time between the departure of a first road user from a conflict zone and the arrival of a second road user at the conflict zone. A PET value of zero indicates a collision (Laureshyn et al, 2016).
- Delta-V: This value models the severity of a potential collision using the speed differences and masses of the two road users involved (see Formula 1). Severity is therefore expressed in units of meters per second. The formula uses the higher speed value as the relevant severity value for the collision. The respective masses, speeds, and the common approach angle are considered (Kizawi and Borsos, 2021; Bahrololoom, Young and Logan, 2020).

Formula 1: Delta-V

$$\Delta v_1 = \frac{m_2}{m_1 + m_2} \times \sqrt{v_1^2 + v_2^2 - 2 v_1 v_2 \cos \alpha}$$

$$\Delta v_2 = \frac{m_1}{m_1 + m_2} \times \sqrt{v_1^2 + v_2^2 - 2 v_1 v_2 \cos \alpha}$$

$$\text{Delta-V} = \max(\Delta v_1, \Delta v_2)$$

where v_1, v_2 are the corresponding velocities, m_1, m_2 the corresponding masses and α the corresponding approach angle of the involved road users.

- Extended Delta-V: This value is based on Delta-V, adjusted to determine the possible severity of an accident in a more nuanced manner. The formula recalculates speeds by multiplying the existing reaction time (e.g., TTC) by an assumed deceleration rate, resulting in reduced speeds. This provides more realistic values in the event of a possible collision (Laureshyn et al., 2017). In this study, only Delta-V was used, as deceleration and other evasive manoeuvres can be captured by the collision likelihood estimation (see Section 5 for further discussion on this decision).

2.2 Video-based conflict analyses

Recent video-based conflict analyses present a mixed picture of attempted implementations. One study conducted a before-after analysis using the PET indicator to gather evidence of changes in the degree of road safety, without addressing broader concerns (Niaki, Dijkstra and Wijlhuizen, 2021). Another study collected descriptive data on traffic flow and speed distribution and analysed conflicts using the PET and TTC indicators (Eberling et al., 2022). Potentially relevant conflicts were identified manually based on low indicator values.

A more critical study mentions difficulties in using automated trajectory evaluation software. Many framework conditions, but especially the distortion of the camera lens, can lead to incorrect distance and speed measurements, particularly when it comes to the indicator TTC, which requires high-quality trajectories. Furthermore, relying solely on the indicator PET does not provide an accurate description of the level of safety. Therefore, it is recommended to include additional criteria, such as speed or type of conflict. However, performing a critical and manual evaluation after obtaining the automated results is still necessary (Steiner et al., 2023).

Currently, Delta-V only considers relative collision damage, and not collision likelihood. TTC and PET only consider the proximity of a conflict by indicating the available time before a collision occurs. An expected collision severity-based analysis (considering both collision likelihood and severity) is therefore not possible. This research aims to fill this gap by proposing a systematized approach by combining the collision severity (approximated by Delta-V) with the collision likelihood (approximated by TTC or PET). This represents an expected severity-based approach to account for both the collision likelihood and severity in proactive safety analysis.

3 Methods

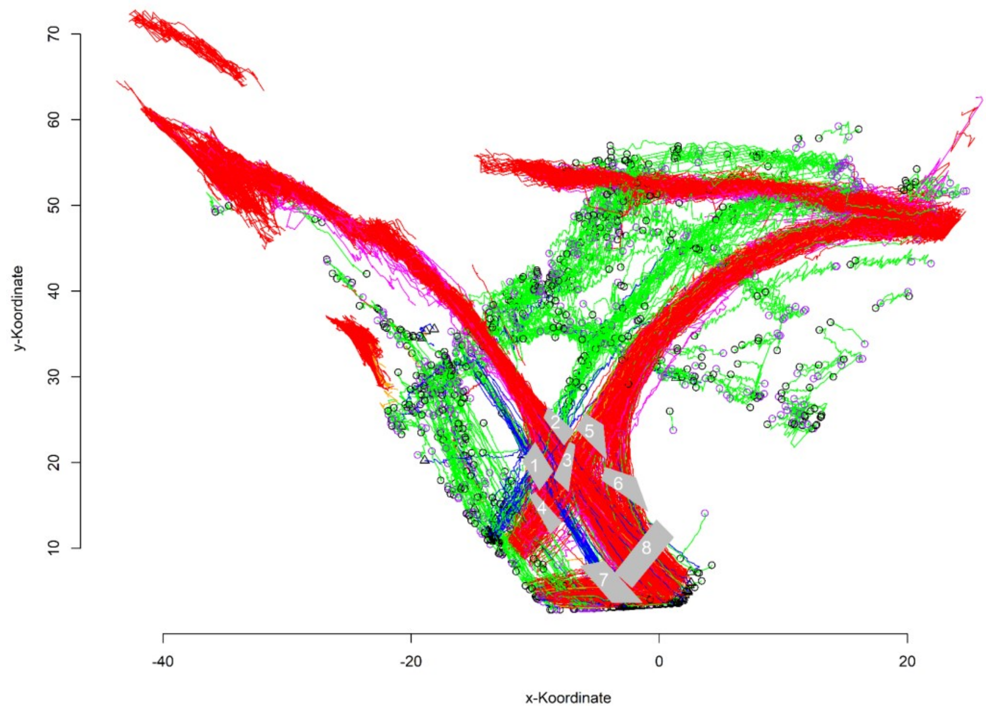
3.1 Field experiment

The field experiment for obtaining conflict data was conducted in Zurich at a node with a high mix of different road users and a history of accidents involving cyclists. The assessed node is similar to a roundabout but has dedicated cyclist lanes and an at-grade crossing of the road and pedestrian sidewalks. Due to the large size of the node (two lanes, four arms, with a diameter of about 50 meters), a focus area was determined (i.e., one arm of the node). The camera used in the field experiment was mounted at a height of 8.5 meters and recorded for one week, resulting in approximately 90 hours of usable video data during daylight hours.

3.2 Trajectory extraction and classification

For video-based trajectory creation, object detection was chosen over feature tracking due to its established methods, better management of obstacles in the image, and ability to detect stationary road users. However, accurate identification requires a high-quality image training dataset. Failure to identify an object in even one video frame will result in an incomplete trajectory (Niaki, Dijkstra and Wijlhuizen, 2021).

The trajectories of the various road users were extracted and categorised using the "object detection" computer vision techniques based on the collected video data. The categorisation includes seven modes: pedestrians, cyclists, motorcyclists, cars, vans, lorries, and buses. Figure 1 shows the output of this step (an aerial image of the same area can be seen in Figure 2). To correct for erroneous classifications, a reclassification was performed using virtual polygons. The virtual polygons (as seen as in Figure 1) allow for the extraction of different driving (or walking) relationships. This allowed, for example, road user trajectories crossing polygons 2 and 1 that were mistakenly classified as “pedestrians” to be reclassified as cyclists.



Extracted trajectories by SLR Engineering
Illustrated by AIT

Figure 1: Sample of classified road user trajectories (blue = cyclists, red = cars, green = pedestrians)

3.3 Differentiation and filtering of conflicts

The conflicts were identified using the established SSMs TTC and PET. Conflicts were then analysed and categorised by traffic mode, type of conflict, and expected severity. Traffic mode refers to the categorised road users (e.g., pedestrian), while the type of conflict was determined by virtual polygons. Each detected road user crossed a start and an end polygon. Each conflict was therefore categorised by four polygons and further categorised as turn-in, turn-off, or intersect conflicts.

Conflicts were identified using a TTC or PET value of less than or equal to two seconds. This is a generous limit but enables comparison of the results with the systematised categorisation of conflicts into dedicated categories of TTC and conflict speeds from literature (Kronprasert et al., 2021).

The expected collision severity was then evaluated using the approach proposed in this paper. The expected severity was computed as the product of the probability of a collision occurring and that potential collision's severity (see Formula 2). The SSMs PET and TTC indicate the probability of a collision, and Delta-V indicates the severity of a collision. The probability increases as the SSMs decrease. The collision probability was calculated using a linear weighting, where a TTC or PET of two seconds resulted in a collision probability of zero, and a TTC or PET of zero seconds resulted in a collision probability of one (i.e., a collision would occur). The collision severity was represented by the speed difference assigned to a conflict participant. This was calculated using the Delta-V value, which requires information on the masses of the individual road users. These masses were estimated in a simplified manner (e.g., car mass = 1,600 kilograms). In this context, the expected severity is the probability-weighted severity of a potential collision, expressed in the speed difference between two road users involved in the conflict (in meters per second).

Formula 2: Expected severity

$$Expected\ severity\ [\Delta\ \text{meters/second}] = \frac{L - SSM}{L} \times DeltaV$$

where L is the corresponding limit for selecting conflicts (here, $L = 2\ seconds$) and SSM the surrogate safety measures "time-to-collision" or "post-encroachment-time", measured in seconds.

To exclude all irrelevant conflicts, minimum velocities, maximum values of SSMs (TTC and PET), and a spatial extent were defined. Conflicts outside the focus area or involving parked cars were excluded. Additionally, to classify the type of conflict, all road users involved in conflicts had to cross two of the virtual polygons. The minimum distance attribute filtered false-positive conflicts, eliminating cases where the TTC was calculated to be lower than it actually was due to the road curvature. The remaining conflicts were considered relevant conflicts.

In summary, video-based conflict analysis was used to determine a qualitative overview of conflict situations at the investigated node. Around 2,000 conflict situations were identified over 90 video-hours using automated software functions and given a time stamp for manual review. A quantitative assessment of the expected collision severity was carried out based on the differentiation of the conflict situations and the expected severity formula proposed in this paper.

4 Results

After identifying the conflicts, they were categorised by conflict proximity (TTC and PET) and potential collision speed (referring to the faster road user involved in the conflict). These were compared with discrete limits for vulnerable road users (pedestrians, motorcyclists, and cyclists) from literature (Sayed and Zein, 1999) (see Table 1). The probability of death for vulnerable road users is thus categorised into four levels: “None” (negligible probability of death), “Low” (5 % probability of death), “Moderate” (10 % probability of death), and “High” (85 % probability of death) (Jurewicz et al., 2016). This discrete categorisation provides a clear understanding of the expected consequences for vulnerable road users. To be assigned to a category, both limits (TTC or PET, and collision speed) must be met. In the 90 hours of video analysed, no conflicts with a high probability of death were observed.

Table 1: Expected consequences of conflicts involving vulnerable road users (pedestrians, motorcyclists, and cyclists)

Likelihood of death	**Number of road users**	**Share of road users (%)**	**Number of conflicts per hour**	**TTC or PET limit (seconds)**	**Collision speed (m/s)**
Negligible	13,852	90.98	164.90	> 2.0	< 5
Low (> 5 %)	1,322	8.68	15.74	≤ 2.0	≥ 5
Moderate (> 10 %)	51	0.33	0.61	≤ 1.5	≥ 8
High (> 85 %)	0	0.00	0.00	≤ 1.0	≥ 14

m/s = speed, measured in meters per second. 1 m/s = 3.6 kilometres per hour.
TTC = time-to-collision. PET = post-encroachment-time.

Table 2 displays the expected collision severity by road user, not limited to vulnerable road users. In addition to the absolute number of conflicts, the proportion of conflict involvement normalised by all detected road users is also shown. The expected severity is summarised as average, 85th percentile, and maximum values. Vulnerable road users were overrepresented in the observed conflicts. This is because they have a higher probability of being involved in such conflicts. Overall, one in eight of all road users were involved in conflicts.

Table 2: Expected collision severity by road user

Involved road user	**Modal Split (%)**	**Number of conflicts**	**Proportion of conflict involvement (%)**	**Expected severity [Δ m/s]**		
				Average	85th percentile	Maximum
Car	73.18	11,019	13.0	0.36	0.74	9.24
Cyclist	10.08	1,749	15.5	0.80	1.52	6.82
Pedestrian	7.43	1,048	12.7	1.01	1.92	8.06
Motorcyclist	2.33	468	18.1	0.67	1.33	8.55
Van	4.14	244	5.0	0.16	0.29	1.53
Lorry	2.81	165	5.2	0.14	0.16	2.83
Bus	0.02	1	5.6	0.00	0.00	0.00
Total	100.00	14,714	12.8	0.46	0.91	9.24

Δ m/s = speed difference, measured in meters per second.

To provide a more detailed analysis, the conflicts were further differentiated based on the combined road users. The result is presented in Table 3, which only includes conflicts involving vulnerable road users. Conflicts between cars and slower road users (i.e., pedestrians or cyclists) occurred most frequently.

Table 3: Expected severity of conflicts for vulnerable road users (pedestrians, motorcyclists, and cyclists) by combined road usage

Involved road user 1	**Involved road user 2**	**Number of conflicts**	**Expected severity [Δ m/s]**		
			Average	85th percentile	Maximum
Cyclist	Car	699	0.90	1.68	6.82
Car	Pedestrian	583	1.13	2.06	8.06
Cyclist	Cyclist	256	0.69	1.30	4.28
Cyclist	Pedestrian	200	0.81	1.73	4.24
Car	Motorcyclist	191	0.61	1.23	3.26
Cyclist	Motorcyclist	49	1.07	2.19	3.34
Motorcyclist	Pedestrian	43	0.99	1.86	4.29
Cyclist	Van	22	0.90	1.64	2.39
Motorcyclist	Motorcyclist	15	0.83	2.08	2.75
Cyclist	Lorry	13	0.55	0.92	1.27
Motorcyclist	Van	8	0.90	1.49	1.74
Pedestrian	Lorry	4	1.36	1.56	1.80
Motorcyclist	Lorry	3	1.49	2.26	2.79
Pedestrian	Van	2	2.23	3.56	4.13
Cyclist	Bus	1	0.57	0.57	0.57
Total	**-**	**2,089**	**0.91**	**1.71**	**8.06**

Δ m/s = speed difference, measured in meters per second.

Figure 2 illustrates the spatial distribution of conflicts and their expected severity on a map. The size and darkness of each point correspond to the expected severity. Expected collision severities were higher at the crosswalks (yellow zebra markings) and where the road crosses the bike lane and pedestrian sidewalk (in the centre of Figure 2).

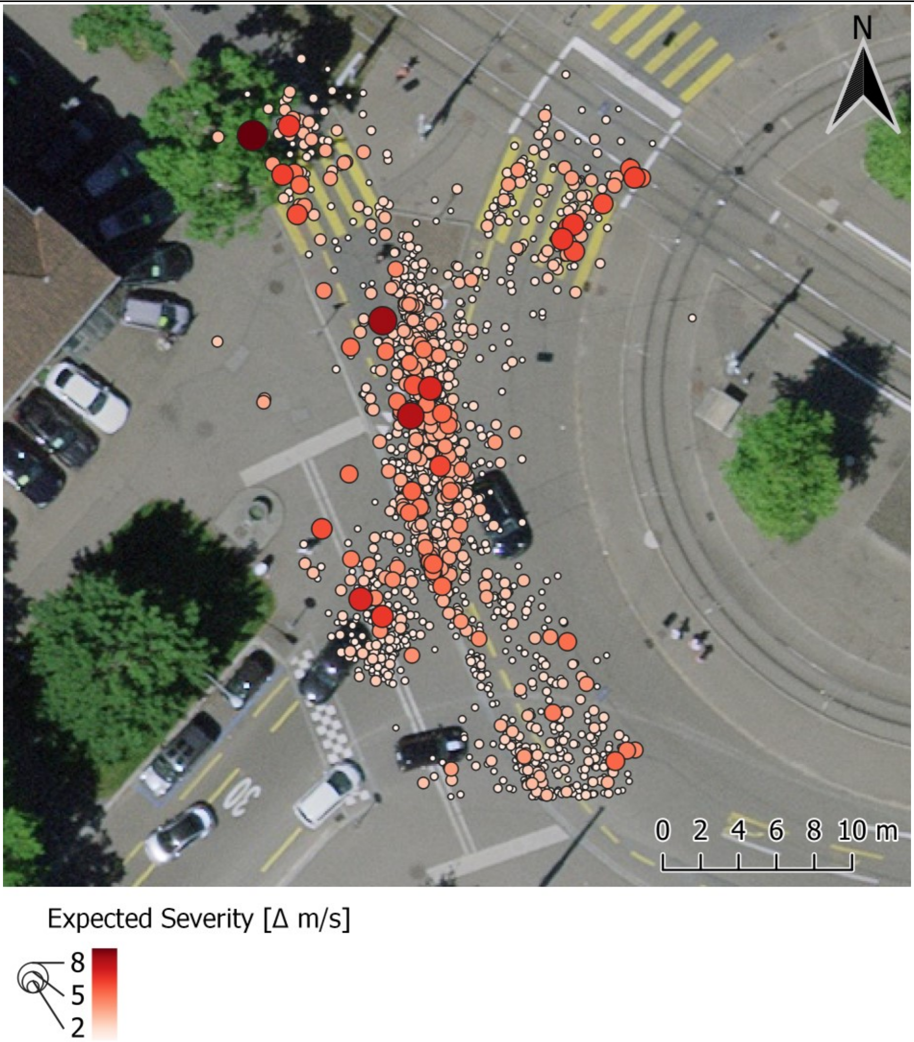


Figure 2: Heatmap of detected conflicts based on expected severity. Δ m/s = speed difference, measured in meters per second

To gain deeper insight into the most relevant conflicts, conflicts with the most common driving relationships and those with the highest expected severity were selected. Conflicts identified by either SSM (TTC or PET values less than or equal to two seconds) were selected. Figure 3 shows an example result, displaying the most common combination of road users turning in and out. The figure illustrates that conflicts occur on the road and where the road crosses cycle lanes and pedestrian sidewalks.

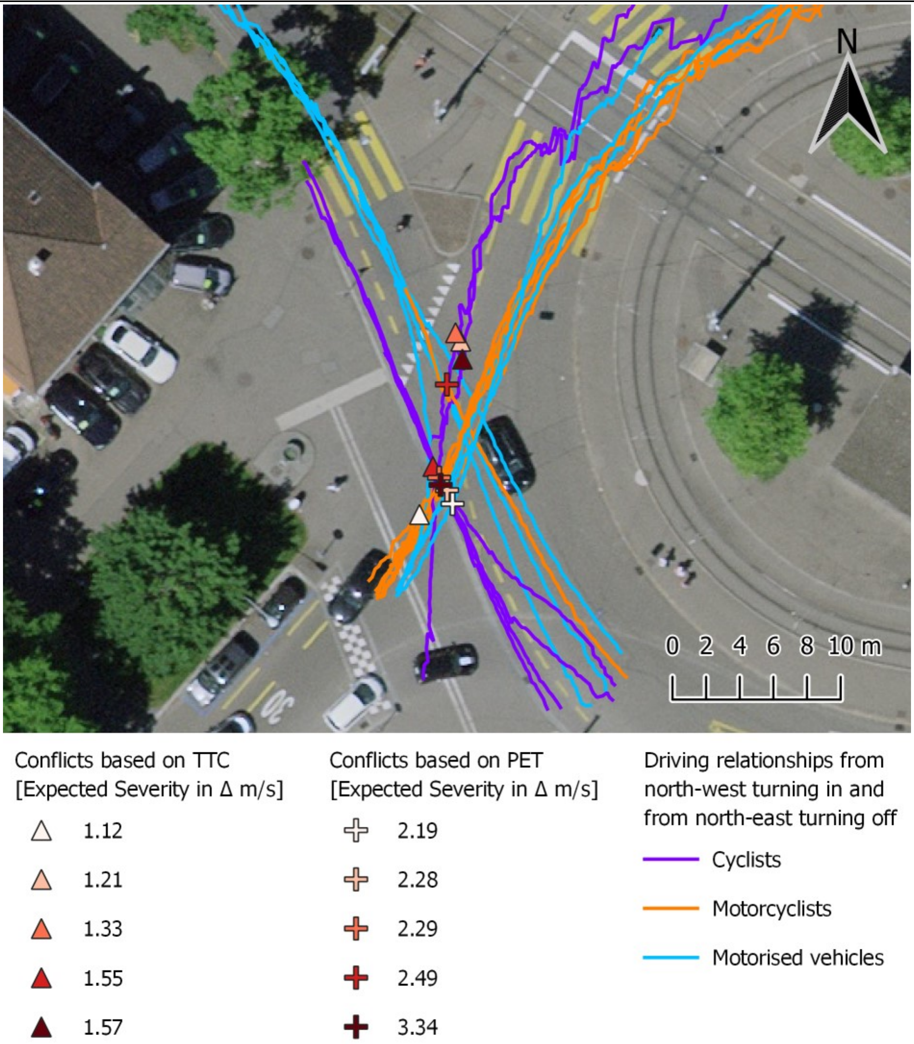


Figure 3: Conflicts with the highest expected severity of the most common driving relationships. Δ m/s = speed difference, measured in meters per second. PET = post-encroachment-time. TTC = time-to-collision

5 Discussion

The analysis indicates that conventional video-based conflict analysis can be expanded to include an improved consideration of expected collision severity. Instead of solely identifying potential conflicts through a SSM, this measure can be combined with the crash severity predictor Delta-V. This combination also allows for the indirect inclusion of evasive manoeuvres: based on expert assessment, a further refinement of the probability calculation derived from the SSMs can reflect possible evasive manoeuvres by the road users involved in the conflict (instead of the linear approximation of collision probability used in this report). This approach will result in a more nuanced expected severity-based analysis. The chosen SSM limit that indicates a conflict can be derived from literature findings (in this report, two seconds was used).

The conducted field experiment demonstrates the success of the proposed approach to some extent. The expected severities of collisions estimated through potential conflicts appear to correspond to registered bicycle collisions, as illustrated in Figure 4. A spatial representation of the node aids road safety professionals in quickly identifying conflict areas and verifying the accuracy of calculated results. The differentiation enables targeted and needs-based analysis of the results. Expected severities can be individually examined and interpreted for each group of road users. Systematically determining the driving relationships between road users allows grouping, summarising, and analysing conflicts within the groups.

This proposed method of video- and expected severity-based conflict analysis has the potential to improve road safety work in Switzerland by proactively preventing accidents and injuries. Many existing safety instruments have been based on observations of accident events and are therefore reactive. A systematic procedure for video-based conflict analysis could be further developed by distinguishing between conflict situations. The expected severity formula developed in this paper allows for the comparison of various traffic situations based on the expected severity and the determination of the urgency of the need for action.

The experiment demonstrates the necessity of careful planning when conducting video analyses. The examination perimeter should be tailored to the aim of the analysis, for example, vulnerable road users or cyclists. Depending on the available camera and the size of the examination perimeter, a suitable focus area must be determined. To ensure clear distinction between individual road users, the camera should be installed at a certain height.

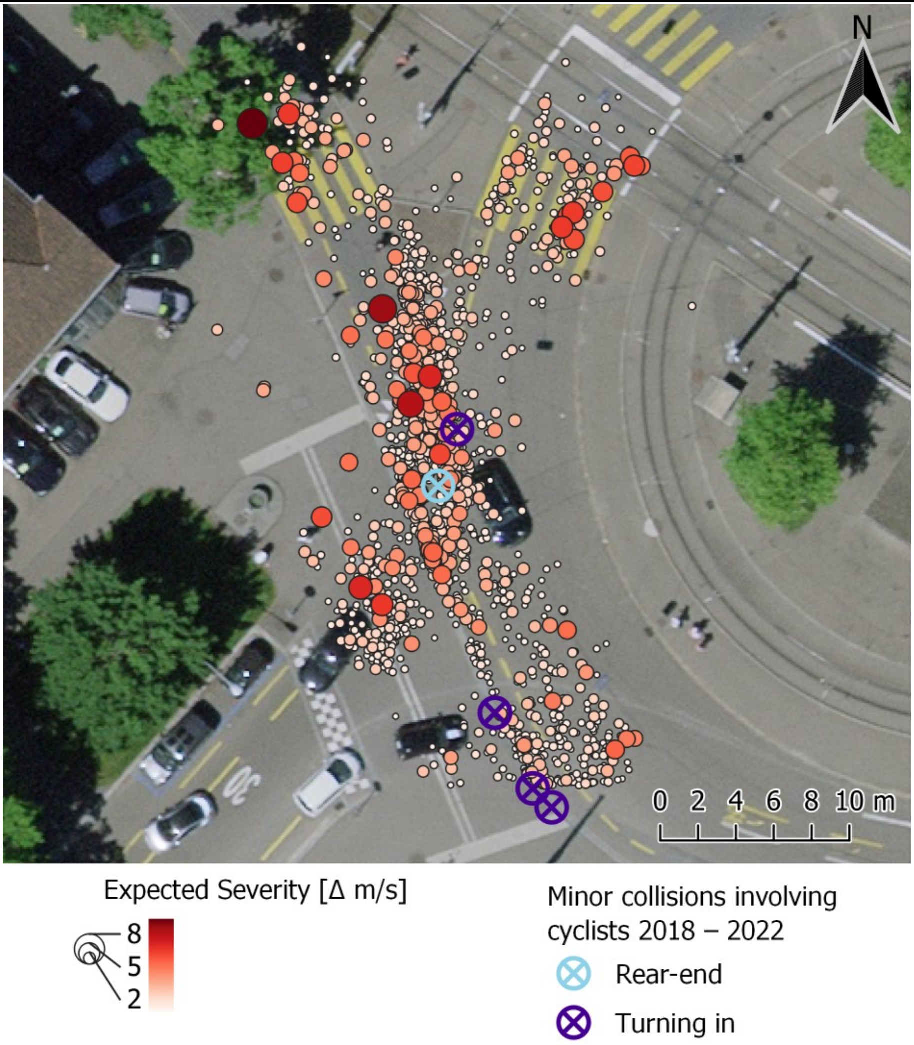


Figure 4: Heatmap of potentially relevant conflicts and registered bicycle collisions. Δ m/s = speed difference, measured in meters per second

The need for further research on fully automated conflict analysis remains significant. One issue is the inaccurate classification of the detected road users, particularly when video data is out-of-focus. This can be addressed by inserting virtual polygons to reclassify misidentified road users. Additionally, overlapping road users can result in imprecise trajectory creation. The algorithm should be improved to include a separate step for smoothing the trajectories. Furthermore, the TTC value is often lower than it would be in reality due to the calculation being based on a straight collision course, which is a specific issue in curved situations. Distinguishing between false-positive conflicts and true-positive conflicts remains a general challenge.

Further studies with application examples are necessary from a scientific perspective to generate more well-founded findings. Guidelines for practical application of video-based conflict analysis do not exist yet and require expert knowledge. A more refined methodology will enable further research such as meta-analyses to compare nodes or node types between cities for benchmarking. Finally, it is important to consider how video-based conflict analysis can contribute to research, particularly how it can be integrated into existing road safety work.

6 Conclusion

Video-based conflict analysis has great potential for proactive accident prevention. It enables differentiated conflict analysis, objective expected collision severity assessment, and targeted measures to improve road safety. The field experiment conducted at a traffic node successfully identified potential collisions and their likelihood. Weighting potential conflicts according to collision severity enabled a more in-depth analysis of the conflict situations. Further work should refine this method of video- and expected severity-based conflict analysis before reliable and fully automated implementation is possible.

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7 Reference list

Bahrololoom S., W. Young and D. Logan (2020) Modelling injury severity of cyclists in bicycle-car crashes at intersections, *Accident analysis and prevention*, **144** (105597).

Eberling P., M. Deublein, M. Brand, A. Renard, A. Machu, R. Weber, P. Saleh, K. Schwieger and A. Schaub (2022) Velo-Infrastruktur-Sicherheitsinstrumente VISSI, Forschungsbericht ASTRA 1730, Bundesamt für Strassen ASTRA, Ittigen.

Hertach P., Y. Achermann Stürmer, R. Allenbach, K. Huwiler, S. Niemann and A. Uhr (2023) Sinus 2023: Sicherheitsniveau und Unfallgeschehen im Strassenverkehr 2022, Beratungsstelle für Unfallverhütung BFU, Berne.

Johansson, R. (2009) Vision Zero – Implementing a policy for traffic safety, *Safety Science*, **47** (6) 826–831.

Jurewicz C., A. Sobhani, J. Woolley, J. Dutschke and B. Corben (2016) Exploration of Vehicle Impact Speed – Injury Severity Relationships for Application in Safer Road Design, *Transportation Research Procedia* **14**, 4247–4256.

Kizawi A. and A. Borsos (2021) Literature review on the conflict analysis of vehicle-pedestrian interactions, *Acta Technica Jaurinensis*, **14** (4) 599–611.

Kronprasert N., C. Sutheerakul, T. Satiennam and P. Luathep (2021) Intersection Safety Assessment Using Video-Based Traffic Conflict Analysis: The Case Study of Thailand, *Sustainability*, **13** (12722).

Laureshyn A., C. Jonsson, T. De Ceunynck, Å. Svensson, M. de Goede, N. Saunier, P. Włodarek, R. van der Horst and S. Daniels (2016) *Review of current study methods for VRU safety: Appendix 6 – Systematic literature review: Surrogate measures of safety in site-based road traffic observations* (Deliverable 2.1 – part 4), Horizon 2020 EC Project, InDeV, Lund University, Lund, Sweden.

Laureshyn A., T. De Ceunynck, C. Karlsson, Å. Svensson and S. Daniels (2017) In search of the severity dimension of traffic events: Extended Delta-V as a traffic conflict indicator, *Accident analysis and prevention*, **98**, 46–56.

Niaki M. N., A. Dijkstra and G. J. Wijlhuizen (2021) Bicycle safety before and after the redesign of intersections in The Hague: Assessment using automated traffic analysis software, Institute for Road Safety Research, SWOV, The Hague.

Polders E. and T. Brijs (2018) *How to analyse accident causation? A handbook with focus on vulnerable road users* (Deliverable 6.3), Horizon 2020 EC Project, InDeV, Hasselt University, Hasselt, Belgium.

Sayed T. and S. Zein (1999) Traffic conflict standards for intersections, *Transportation Planning and Technology*, **22** (4) 309–323.

Steiner R., G. Benedek, M. Doerfel, M. Hackenfort, J. Leitner and B. Lüthi (2023) Alternative Methoden zur Messung lokaler Verkehrssicherheit, Forschungsbericht ASTRA 1746, Bundesamt für Strassen ASTRA, Ittigen.

8 Glossary

Δ m/s	Speed difference, measured in meters per second
AIT	Austrian Institute of Technology
BFU	Beratungsstelle für Unfallverhütung (Swiss Council for Accident Prevention)
Delta-V	Speed difference of two road users involved in an inelastic collision (see Formula 1)
ETH	Eidgenössische Technische Hochschule (Swiss Federal Institute of Technology)
PET	Post-encroachment-time (a surrogate safety measure, see Section 2.1)
SLR	SLR Engineering GmbH in Graz
SSM	Surrogate safety measure
TTC	Time-to-collision (a surrogate safety measure, see Section 2.1)