Bicycle crash analysis using instance segmentation

Introduction

Bicycle usage carries several benefits, from less traffic congestion in cities, less polution, healthier lifestyle, among others. However, cyclist are vulnerable road users, which crash rate is in increase [Eco24][1]. For this reason, research in the field of bicycle crashes during the 15 last years have gained popularity. Within the types of bicycle crashes, one that stands out is the single-cyclist crash, where no other road user is involved.

The lack of data of these events is commonly discussed in the literature [Utr20][2]. However, no solutions have been provided, and recreating crashes lead to dangerous situations for test subjects even in laboratory controlled setups. For this reason, we propose a solution based on publicly available videos of single-cyclist crashes.

To this end, we create a dataset of single-cyclist crashes from web sources. Videos are annotated for computer vision tasks, and used to create motion data. With this, we analyse the motion of the wheels and identify crash events.

Methods

For this research we have manually selected videos from public domain sources. Selected videos contain bicycle crashes where no other road user is involved, or their participation in the event is assumed as a passive perturbation. A dataset of single-cyclist crashes is created from these videos, which include the reference to the video and the time stamp of the crash.

The dataset was annotated using CVAT for instance segmentation in YOLO format. Using this approach, we label the wheels as ellipses using 'front' and 'rear' as features. In addition, we annotate no-crash videos of similar nature to include into the dataset to contrast normal riding motion against crash motion.

Results

The data obtained is the x and y position of both wheels, along with the ratio between axes and the angle of the ellipse. In addition, we calculate the distance between both wheels in time and the slope of the curve.

Figure 1 shows the data of a 'pitch-over' crash. Pitch-over is a crash motion where, due to excessive longitudinal load transfer, the rear wheel lifts from the ground and the bicycle rotates around the contact point of the front wheel.

We observe that after frame 100, the rear wheel moves forward to the front wheel. In line manner, between frame 85 and 105, there is a major increase in the vertical position of the rear wheel. Furthermore, the peak difference between the wheels is equivalent to a 282% with respect to the average difference.

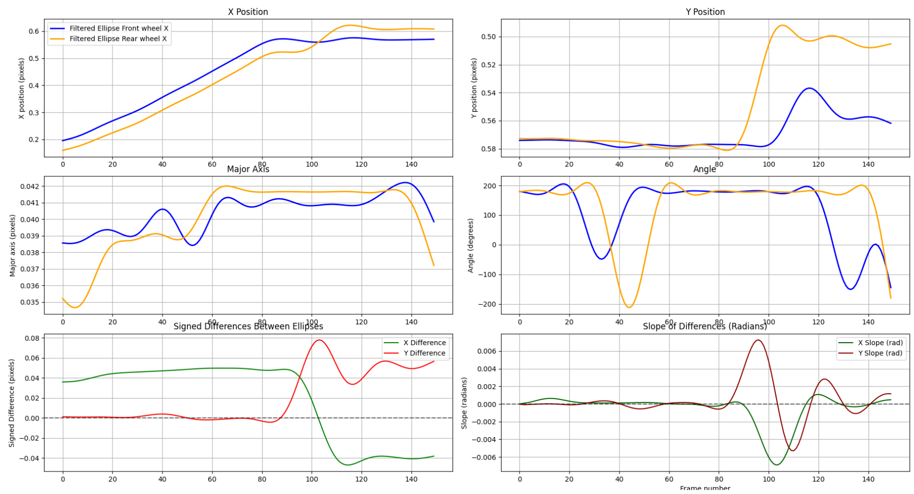

Figure 1: 2-dimensional data from monocular video.

It is important to note that the origin of the reference frame is on the top left corner, however, to simplify the analysis, the y axis was inverted for a more intuitive reading.

Following the same methodology, we extract data from more videos of the dataset. The main findings are summarised in the table below.

Table 1: Distance between wheels from crash videos.

Number	Type	Avg x diff.	Avg y diff.	Max x %	Max y %
1	Pitch-over	-0.08	0.08	-93.2	178.5
3	Start riding	-0.07	0.01	-10.3	226.1
5	Pitch-over	0.02	0.02	167.7	282.7
6	Pitch-over	-0.1	0.03	-93.7	577.7
7	Pitch-over	0	0.01	-844	1203.2
8	Lost control	0.01	0.06	1142	196
9	Pitch-over	-0.09	0.04	-84	141.6
10	Disengagement	-0.04	-0.01	-57.7	-309.9
11	Pitch-over	0.01	0.01	412.9	1286.6

For all crash scenarios, the maximum y difference with respect to the average surpasses 100%.

Table 2: Data of no-crash videos.

Number	Avg x diff.	Avg y diff.	Max x %	Max y %
1	0	-0.01	559.4	-88.5
3	-0.3	0	-15.4	1832.4
4	-0.38	0	-79.5	-1078.6

Discussion

Preliminary results shown in this work are promising, offering a new approach for already identified problems in the field of bicycle safety. Problems addressed in this research are bicycle crash detection and the lack of single-cyclist real-world crash data. Additionally, this represents the first dataset composed only of single-cyclist crashes.

Initially, we have been able to distinguish crash and no-crash scenarios from 2-dimensional wheel positions. We observe that crash scenarios present higher average variations in the motion of the wheels. Furthermore, pitch-over crash configurations always show variations over 150% with respect to the average difference. In line manner, the average difference for both directions (x and y) is greater than 0.01 pixels. Contrarily, no-crash scenarios tend to show average differences below 0.01 pixels for one of the directions.

Limitations

This work faces several limitations that are not fully covered in the preliminary results.

First, the full dataset now comprises 100 videos of single-cyclist crashes, however, we have used only 9 of these for analysis. Similarly, for no-crash events, we have used only three samples.

Second, the videos that more information provide are side-view videos, which offer a clear image of the wheel as an ellipse. On the other hand, longitudinally-recorded videos present the challenge of annotate an ellipse in a shape that is not one.

Third, this approach neglects the rotation of the wheels, which leads to not detecting the longitudinal slip of the wheels.

Fourth, since our dataset is made mainly from dashcam videos, we assume a frame rate of 30 FPS, which is not ideal for crash analysis.

At last, the motion of the camera could lead to outliers where no-crash videos generate data with variations similar to crash videos (see Table 1).

To summarise, the presented methodology allows to gather data from real-world scenarios. Results show that the obtained data is useful for analysis and could be enhanced if challenges are tackled up. Integrating different techniques into the pipeline used in this work, several of the mentioned challenges can be solved. This research will continue in development to enhance results.

Conclusion

In this work, a dataset of single-cyclist crash videos have been created. Using computer vision techniques on these videos, we extract 2-dimensional motion data of the wheels. Then, we analyse the motion of the wheels in different crash scenarios. We conclude that crash configurations where large vertical motions occur are easier to identify. Further work will be to assess near-miss situations and apply triangulation techniques to generate 3-dimensional data.

References

[1]: European Commission (2024) Facts and Figures Cyclists. European Road Safety Observatory. Brussels, European Commission, Directorate General for Transport.

[2]: Utrianen, R. (2020) Characteristics of Commuters' Single-Bicycle Crashes in Insurance Data.