Bachelor thesis report

Quantitative cyclist interaction behavior in bidirectional encounters

Derived from a controlled laboratory experiment of bidirectional encounters

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Abstract

In most large cities, the proportion of bicycle traffic steadily grows each year. This can lead to bicycle path congestion, which will hinder the bicycle traffic. City planners use cyclist traffic models to assess the performance of cycling infrastructure and to manage bicycle and mixed flows. Knowledge on individual cyclist interaction behavior should underpin the bicycle flow models. There is however, in literature, hardly any knowledge available on individual cyclist interaction behavior. More knowledge on this subject will contribute to better bicycle flow models. With these better models, the city planners will get a better picture of the bicycle traffic flows and subsequently new cycling infrastructure can be planned more effectively by the city planners. This will allow large cities to cope with the increasing demand in bicycle traffic. In this research, cyclist interaction behavior data, in face-to-face encounters, from a controlled laboratory experiment is studied to achieve a better understanding of individual cyclist interaction behavior. Several interesting behavioral laws are quantified. The quantitative behavior of cyclists was defined by several factors regarding the behavior of cyclists in space. The factors are collected and visually represented. The boundaries which were found can be used as rules to be included into a behavioral bicycle traffic model. It was also found that steering plays a significant role, since it was shown that it indicates the movement that the cyclist is about to make. This means that the steering angle is the determining factor for cyclists' interaction behavior in bidirectional encounters. Future research should further inspect the steering behavior. In this research, only some qualitative results for the steering behavior were obtained. An effective manner to analyze the inaccurate steering angles should be developed.

Introduction

In most large cities, the proportion of bicycle traffic steadily grows each year. In figure 1, this increasing demand in cycling traffic is illustrated for London. As you can see from the graph, the number of bicycle journeys has almost doubled from 2001 to 2011. You can also see that the number of bicycle journeys will continue to increase exponentially in the years after 2011, according to the projection. In Amsterdam this similar trend is illustrated by figure 2. In figure 2 the share of total journeys for each transportation mode is given for different time periods. It is clear from the figure that the share of bicycle journeys increases over time, from 17% in 1986-1991 to 27% in 2015. In other large cities similar trends are observed. This can lead to bicycle path congestion, which will hinder the bicycle traffic.

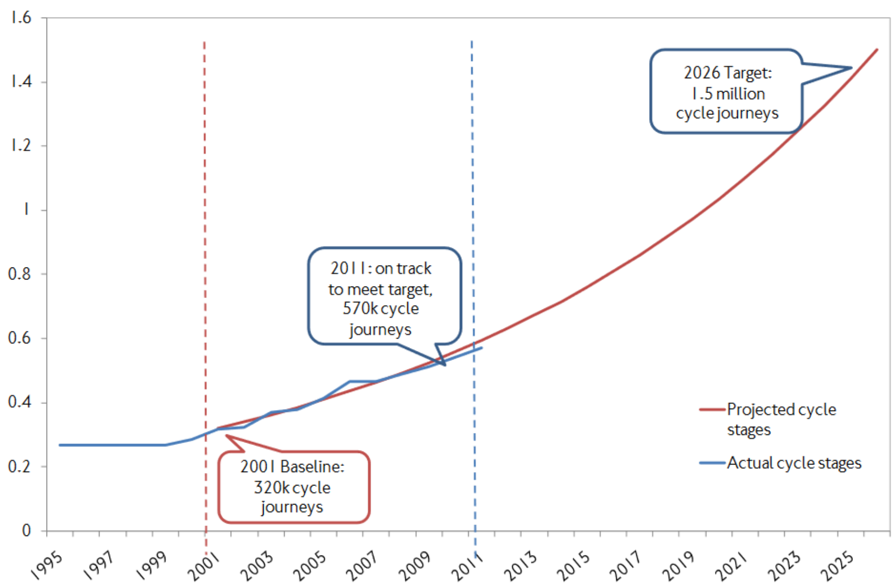

Figure 1 - Cycling traffic in London (TfL_Group_Planning, 2011)

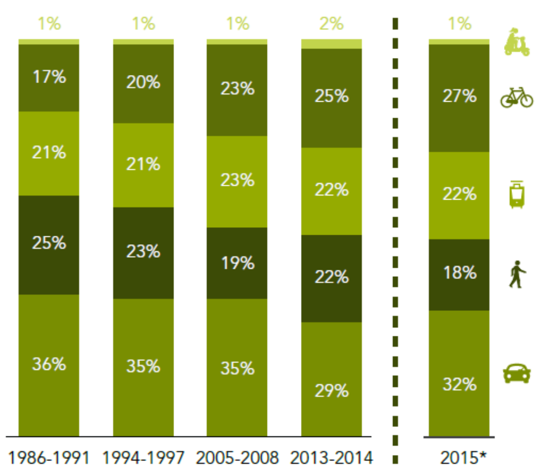

Figure 2 - Modal split Amsterdam 1986-2015 (Gemeente_Amsterdam, 2016)

City planners use cyclist traffic models to assess the performance of cycling infrastructure and to manage bicycle and mixed flows. These models should be as accurate as possible to be able to cope with the increasing demand in bicycle traffic. Knowledge on individual cyclist interaction behavior should underpin these models. According to Yuan et al. (Yuan, Daamen, Goñi-Ros, & Hoogendoorn, 2016) there is however, in literature, hardly any knowledge available on individual cyclist interaction behavior. Research has been done on bicycle traffic flow, but most of the research focused on quantifying macroscopic characteristics of bicycle traffic flow, such as free speed, saturation flow rate and capacity (Gould & Karner, 2009; Hoogendoorn & Daamen, 2016; Parkin & Rotheram, 2010; Raksuntorn, Khan, Trb, & Trb, 2003; Seriani, Fernandez, & Hermosilla, 2015).

Local governments of large cities would be very interested in improving their cyclist traffic models to be able to cope with their increasing cyclist traffic demand, so they would probably want to invest in research towards cyclist interaction behavior. Subsequently, an overall improvement of the cycling infrastructure is to be expected in these cities, affecting the current cycling infrastructure users and attracting new users. Users of other modes of transport will also be affected by this shift in mode choice, car drivers for example will most likely experience less traffic on the roads as it is an alternative for cycling in big cities. A possible other client then local governments will be research institutes. As current information on individual cyclist interaction behavior is lacking, research institutes are likely to provide budget. For example, Allegro: “Unravelling slow mode traveling and traffic: with innovative data to a new transportation and traffic theory for pedestrians and bicycles” would possibly be interested in this research as this research has the purpose described by Allegro.

Data from previous research (Yuan et al., 2016), will be used in this research. Trajectory data of cyclists in a Cartesian coordinate system was obtained in a controlled laboratory experiment by Yuan et al. (Yuan et al., 2016). For the experiment setup and the trajectory dataset derivation one could consult Yuan et al. (Yuan et al., 2016). In Yuan’s research (Yuan et al., 2016), several scenarios are performed. Only the face-to-face, or to say bidirectional scenario is used in this research. From studying cyclist behavior in this type of encounters, several interesting behavioral laws will be quantified. These quantified behavioral laws can be used as rules to be included into a behavioral bicycle traffic model. During the controlled laboratory experiment, the conditions were constant and each cycling maneuver was performed multiple times to limit the effect of inter-personal and intra-personal variability. The inter-personal and intra-personal variability could however still have some influence, thus the data needs to be assessed critically. Especially the learning effect, as the participants watch and learn from other participants, could have a significant influence. However, Andresen et al. (Andresen, Chraibi, Seyfried, & Huber, 2014) used a controlled laboratory experiment to validate and calibrate his model for acceleration and following dynamics for cyclists. Seriani et al. (Seriani et al., 2015) used a controlled laboratory experiment to estimate the capacity of a cycle lane. Both experiments provided useful insights, underlining the applicability of a controlled laboratory experiment concerning cyclist behavior.

Literature review

The main question to be answered in this research is: "What is the quantitative behavior of cyclists in a face-to-face encounter and what role does the steering angle have?" A trajectory set from Yuan's (Yuan et al., 2016) controlled laboratory experiment might look like figure 3 when plotting the coordinates of the data. Some relevant factors are denoted within the figure. According to Yuan (Yuan et al., 2016), the steering angle might play a significant role in traffic operations. This is why the steering behavior is incorporated into the main question. In the work of Gould (Gould & Karner, 2009), a simulation model for bicycle flow is calibrated and validated with field data. In this cellular automaton model, 1.2 m is used as width for a single bicycle flow lane. As motivation, Gould referred to another study, from 1972, which based the lane width finding largely on German design guidelines from that time. One could argue this motivation. Zhao (Zhao et al., 2013) also used cellular automaton. Zhao modelled passing events mixed bicycle traffic, consisting of conventional bicycles and electronic bicycles. A single bicycle flow lane width of 1 meter was used, referring to AASHTO (AASHTO, 2010). AASHTO does not specify any derivation of this particular distance. Analyzing lateral interaction and lateral deviation distances in bidirectional encounters, as denoted in a presumed model in figure 3, will provide insight in the lateral space which cyclists need to not interact with each other. The location and magnitude of deviation distances could be used in studies like that of Gould (Gould & Karner, 2009) or Zhao (Zhao et al., 2013) to determine single bicycle flow lane widths or passing lengths for bi-directional encounters. The steering behavior could be used to determine the viewing distance that cyclists need to react on oncoming cycling traffic, since steering would be the first reaction to start evading.

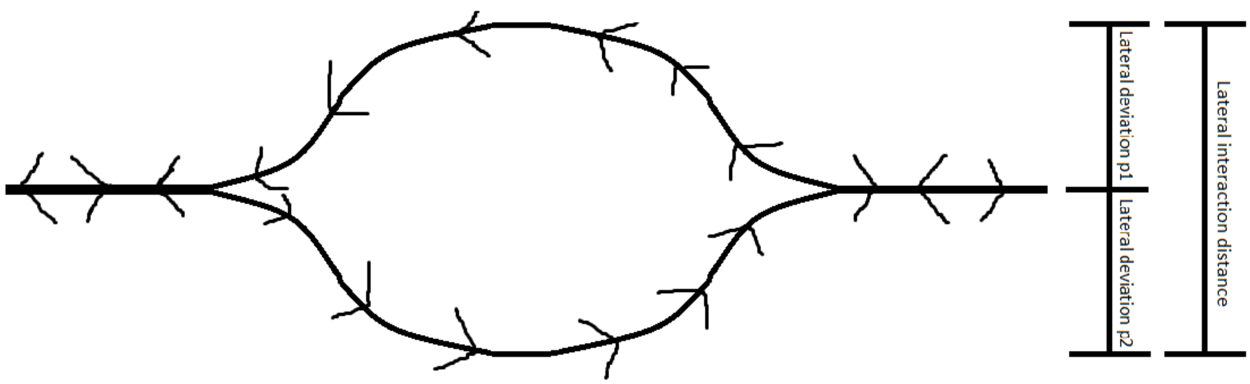

Figure 3

The literature review yields the following sub-questions for the data analysis, in accordance with the main question: "What is the quantitative behavior of cyclists in a face-to-face encounter and what role does the steering angle have?"

- What is the maximum lateral deviation?
- How do corresponding maximum lateral deviations relate in space?
- Where do cyclists move after maximum lateral deviation?
- What is the lateral interaction distance?
- When do cyclist start steering to evade?
- Where do cyclists start steering to evade?

Methodology

The trajectories which resulted from the experiment of Yuan et al. (Yuan et al., 2016) are used in answering the sub-questions. The answers on the sub-questions lead to answering of the main question. All the needed information is extracted from the Cartesian trajectory data.

Space factors

Every quantitative space factor which is used in the sub-questions and thus is to be determined, is given in table 1. In the first column, the factor is denoted. In the second column, the way of processing the data to obtain a quantitative result for the factor is described. When analyzing the maximum lateral deviation and the interaction distance, the influence of gender is analyzed to determine whether there is an influence of gender on the evading behavior.

Factor	Data analysis
1. Maximum lateral deviation	Maximum y-position difference between the middle line and the actual trajectory
2.Interaction distance	y-positions difference at the location where time and x-dimension of corresponding trajectories are equal
3.x-difference maximum lateral deviations	Difference in x-dimension between the x-locations of the maximum lateral deviations for two corresponding trajectories
4.x-movement after maximum lateral deviation	Difference in x-dimension between the x-location of the end of the trajectory and the x-location of the maximum lateral deviation
5.y-movement after maximum lateral deviation	Difference in y-dimension between the y-location of the end of the trajectory and the y-location of the maximum lateral deviation

Table 1 - Methodology space factors

There are some terms used in the data analysis which require some clarification. As described in the data description chapter, there are 96 head trajectories, they form 48 couples. Corresponding trajectories or trajectory couples are two head trajectories which formed a couple during the experiment. The middle line is used to determine the maximum lateral deviation and is defined as the mean y-value of two corresponding trajectories at the start. Trajectory couples start approximately directly opposite of each other, but there may be some variation. To account for this variation, a middle line between the two starting points is computed. The starting location of a participant may vary per trajectory couple too. This is the reason why a middle line which varies per trajectory couple has been chosen.

Steering angle

As is explained in the data description chapter, there are four points on each participant for each run. For these points, the x- and y-location over time are known. The four points for a certain time instance are displayed in figure 4. For a certain equal time instance t, you have the head point, the right handle point and the left handle point. The fourth point is the head point one time instance earlier than the time instance for the other three points. A longitudinal and lateral vector are defined to compute the steering angle. The lateral vector is calculated by subtracting the left steering handle x- and y-values from the right steering handle x- and y-values. The longitudinal vector is calculated by subtracting the head x- and y-values one time instance behind t from the head x- and y-values at time t. The steering angle in degrees, for the time instance t, is computed by subtracting 90 degrees from the angle “A”, depicted in figure 4.

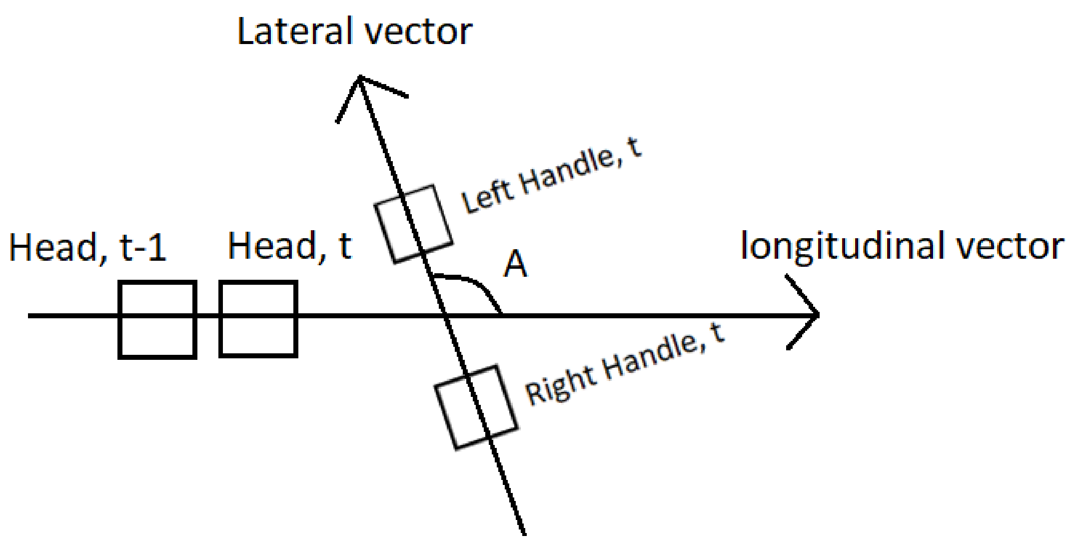

Figure 4 - Steering angle definition

The role of steering behavior is analyzed by taking a look at the time and location where participants start to steer to evade. The location factor is researched by comparing the location where participants start to steer to evade and the location of where the evading clearly shows on the trajectory. The time factor is researched by comparing the moments when participants start to steer to evade, between different trajectory couples.

Data description

In the experiment conducted by Yuan et al(Yuan et al., 2016), 48 runs were done for the bi-directional interaction case. On each of the 48 runs, 2 participants participated. On each participant, 4 points were distinguished. These are the Head point, the rear point, the right handle point and the left handle point. Each point on each run was captured by cameras. By making use of video processing tools, trajectories, projected onto ground level, for each point on each run were obtained. A small part of the resulting data is displayed in figure 5 to illustrate the used data.

	1	2	3	4	5	6	7	8	9
1	6392	407.8333	930.3333	0	1045	290.2911	95.5730	7.3646e+05	438.3670
2	6393	430.8000	923.6000	0	1045	313.2850	98.4260	7.3646e+05	438.4390
3	6394	447.1667	920.1667	0	1045	328.9879	101.1927	7.3646e+05	438.5190
4	6395	472.8000	919.6000	0	1045	351.4778	109.3370	7.3646e+05	438.5810
5	6396	485	918.5000	0	1045	362.3856	112.7292	7.3646e+05	438.6390
6	6397	548	919.8000	0	1045	416.4179	135.0569	7.3646e+05	438.7260
7	6398	560.5000	920.5000	0	1045	426.7230	139.5967	7.3646e+05	438.7900
8	6399	572.6000	920.2000	0	1045	437.3155	143.7872	7.3646e+05	438.8480
9	6400	586.2000	921.4000	0	1045	448.5918	149.2258	7.3646e+05	438.9060
10	6401	623.1667	924.1667	0	1045	479.4208	164.0046	7.3646e+05	438.9890
11	6402	649.6000	925.2000	0	1045	501.9053	173.9846	7.3646e+05	439.0450
12	6403	674.5000	926.5000	0	1045	523.2048	183.1178	7.3646e+05	439.1290
13	6404	701.4000	926.8000	0	1045	546.4682	192.8496	7.3646e+05	439.1790
14	6405	715.6000	928.2000	0	1045	558.3158	198.9308	7.3646e+05	439.2680
15	6406	728.5000	927.5000	0	1045	569.8994	202.5953	7.3646e+05	439.3640
16	6407	753.4000	927.8000	0	1045	591.6693	211.4850	7.3646e+05	439.4080
17	6408	779.4000	927.8000	0	1045	614.2292	220.4094	7.3646e+05	439.4580
18	6409	803.8333	927.3333	0	1045	635.9064	228.4824	7.3646e+05	439.5270
19	6410	816.5000	926.5000	0	1045	647.4894	232.4060	7.3646e+05	439.6040
20	6411	831.2000	927.4000	0	1045	660.0358	237.9424	7.3646e+05	439.6920
21	6412	856.6000	926.8000	0	1045	682.6239	246.4237	7.3646e+05	439.7390
22	6413	881.5000	926	0	1045	704.8578	254.3127	7.3646e+05	439.8220
23	6414	907.5000	925.5000	0	1045	727.9770	263.2417	7.3646e+05	439.9000

Figure 5 - Resulting Data

Column 5 contains the ID-numbers. Each point on each run has a different ID-number, which is why this is used to find the other data for a certain point on a certain run. The other used data in this thesis are the x-location, the y-location and the time. The x-location is contained within column 2, the y-location in column 3 and the time is contained within column 9. All this data was processed through Matlab to obtain the results.

Results

From the data of the experiment conducted by Yuan et al. (Yuan et al., 2016), the trajectories depicted in figure 6 are obtained. The trajectories which have been computed are the trajectories of the head positions. The head position is the most central point on the bicycle, which is why it has been chosen to plot the trajectories. As can be seen, the participants mostly started around the center line of the bicycle path at 9.84 m in Y-dimension. From their starting points, they cycled face-to-face with another cyclist and interacted to avoid collision. In the legend, the general direction of movement is given.

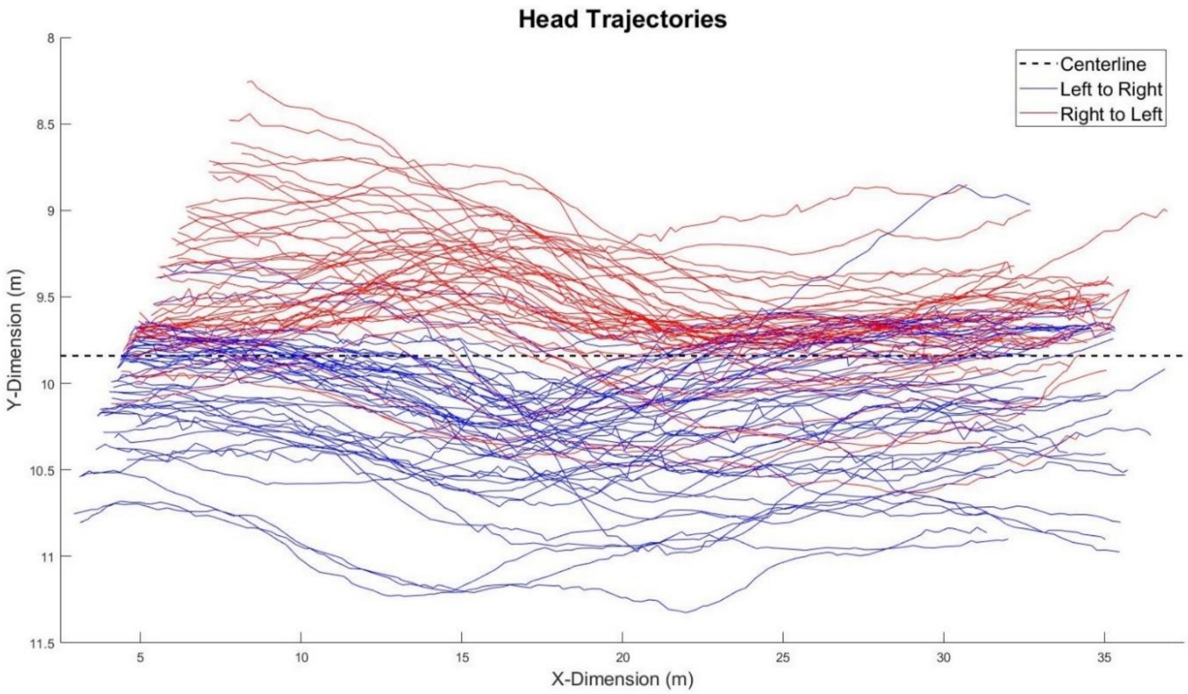

Figure 6 – Head trajectories

To be able to obtain quantitative cycling behavior from the data, five factors regarding space have been researched and two regarding the steering angle. This was also already stressed out in the methodology. To determine the space factors, the head position is used again to obtain trajectories, since it is the most central point on the bicycle. At first the factors regarding space will be discussed, then the factors regarding the steering angle.

Space factors

In table 2, certain statistical data is summed up for each of the five space factors. The 50th percentile or median is chosen to show a typical value for the corresponding factor. The 5th and 95th percentile are chosen to define boundaries for the factors, eliminating big outliers. In figure 7, every maximum lateral deviation for each participant in each run is displayed in histograms. Gender has been distinguished to determine the influence of gender on the evading behavior. The difference in gender can be observed from the histograms in figure 7. The histogram of the female participants is shifted to the right, compared to the male histogram. The averages for the different gender groups have also been computed. For males the average is 0.61m and for females this is 0.70m. This means that women generally evade more than men. Statistical values without gender division are given in table 2.

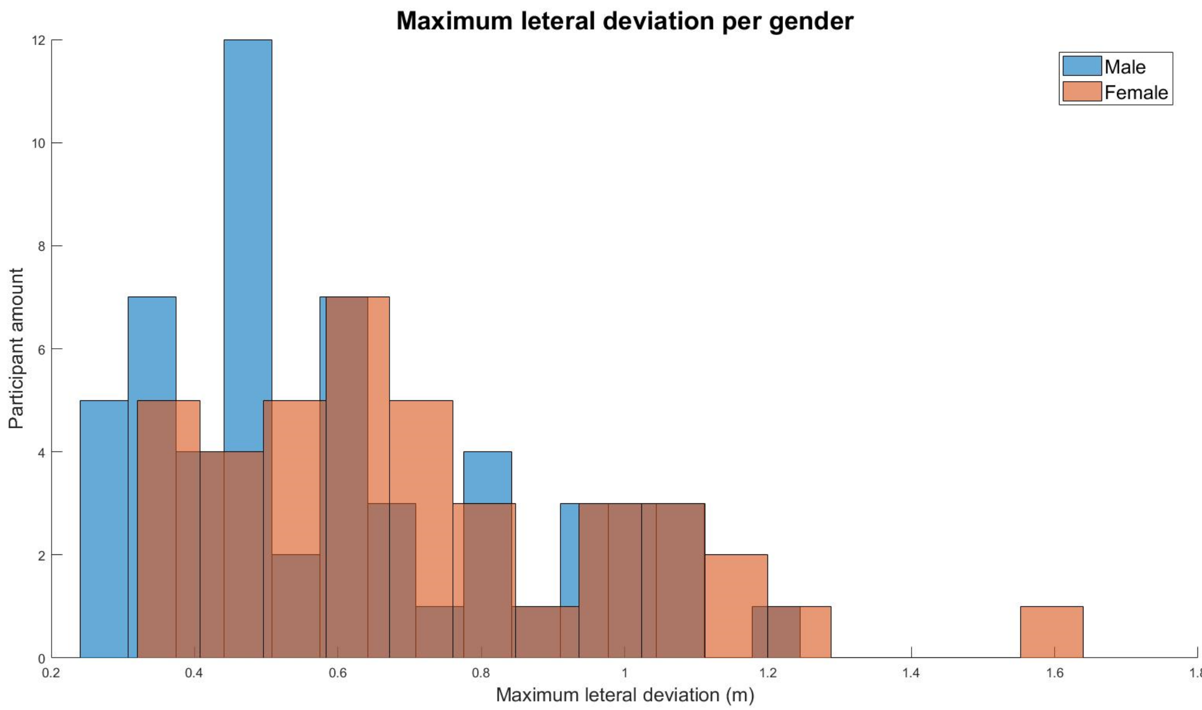

Figure 7 - Histograms lateral deviation

From the lateral interaction distance, it can also be observed that women generally evade more than men. The average in male-male encounters is 0.79m. For male-female encounters the average is 0.97m and for female-female encounters the average is 0.99m. Some other statistical data is represented in boxplots in figure 8 and in table 2. It is observed by comparing the male-female boxplot and the female-female boxplot that they are quite similar, having medians which correspond well with each other. This suggest that the presence of a women is the dominant factor for the interaction distance, contrary to the presence of a male.

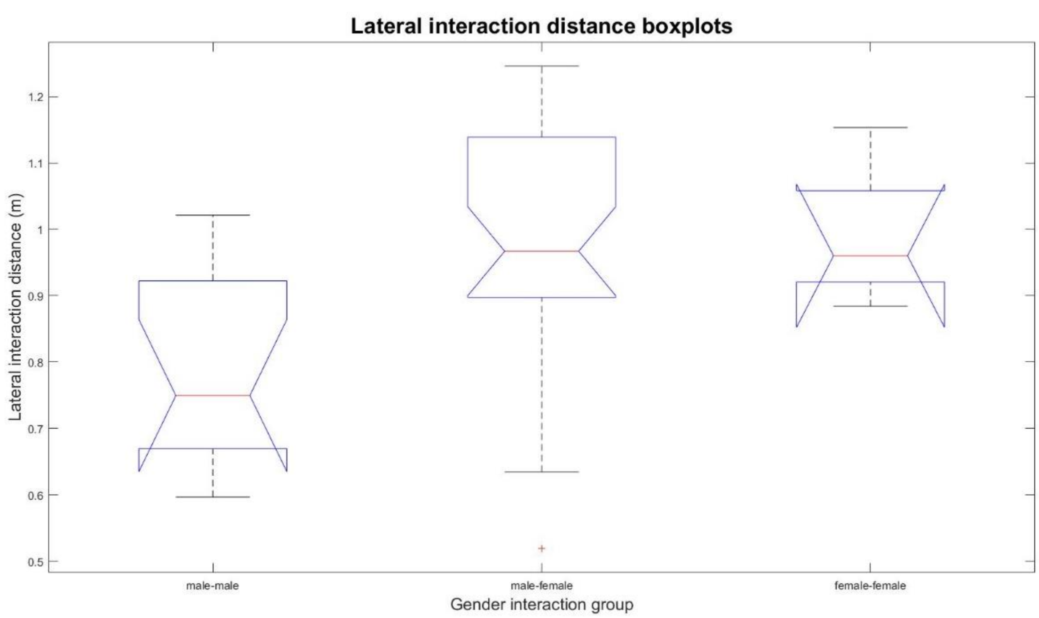

Figure 8 - Boxplots lateral interaction distance

Another observation that can be made is that, on average, the maximum lateral deviation does not take place at the moment when cyclists pass each other. Otherwise the lateral interaction distance would have equaled two times the maximum lateral deviation. To find out where it actually does take place, the difference in x-location between the two maximum lateral deviations for each trajectory couple has been studied. Certain statistical values for this factor have been found and are displayed in table 2. The difference in y-location is just the sum of the maximum lateral deviations and statements about this can already be made by studying the maximum lateral deviation.

In determining where maximum lateral deviation takes place, it is also interesting to take a look at the movement after maximum lateral evading. The x-movement and the y-movement have been researched. Again, certain statistical values for these factors are displayed in table 2. Some more interesting statistical values are that 15 percent of the participants does not move in y-direction after maximum lateral evading. In x-direction, 11 percent of the participants does not move after maximum lateral evading. This means that 11 percent of the participants continues evading from the middle line until the end and 4 percent follows a straight line after maximum lateral deviation. This suggest that for the 11 percent which continued evading, the observation area was not big enough to fully capture their evading behavior.

	1. Maximum lateral deviation	**2.Interaction distance**	**3.x-difference maximum lateral deviations**	**4.x-movement after maximum lateral deviation**	**5.y-movement after maximum lateral deviation**
5th percentile	0.30	0.61	-6.65	0	0
50th percentile	0.60	0.95	4.72	10.78	0.30
95th percentile	1.13	1.20	22.99	22.03	0.75

Table 2 - Statistical values for factors regarding space (dimensions in meter)

In figure 9, an actual trajectory set which corresponds quite well with the median values of all the space factors stated in table 2 is displayed. Each factor has been assigned a number in table 2, they correspond to the numbers depicted in figure 9. Figure 9 gives a visual representation of the space factors.

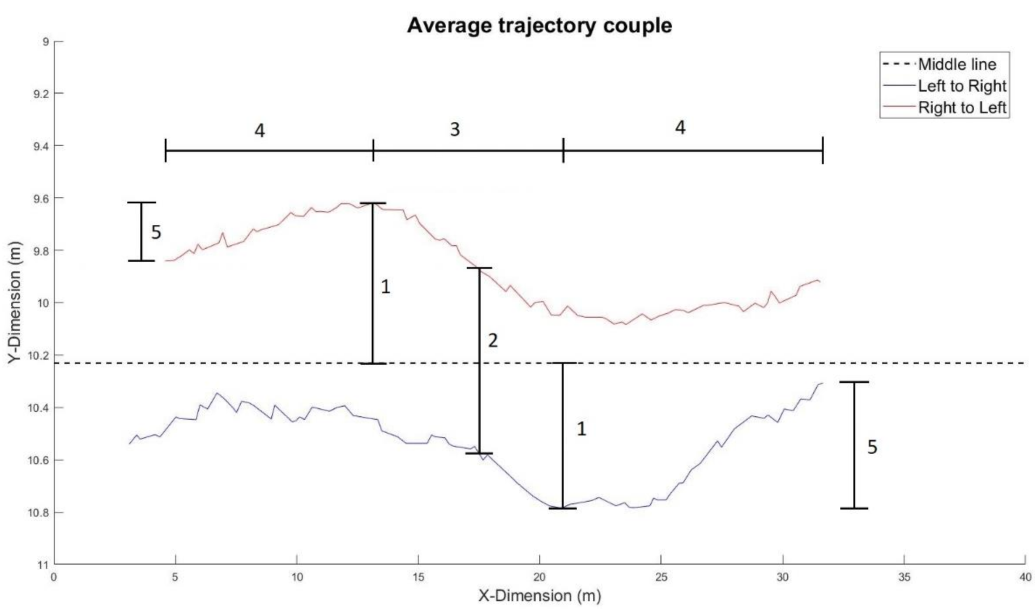

Figure 9 - Typical trajectory with space factors

Steering angle

The steering behavior proved to be very much heterogenic. Furthermore, the data used to obtain the steering angles has some inaccuracies. Slightly inaccurate coordinate data translates in big inaccuracies for the steering angle, since the steering angle is defined on small scale. This is why no general quantitative behavior is obtained. Nevertheless, there have been obtained some interesting results regarding the time and location with respect to the steering angle. The steering behavior has been determined by categorizing trajectories in combination with the steering angle. Two categories have been distinguished, these are abrupt steering behavior and gradual steering behavior. In the steering angle graphs which occur in figures 10 to 13, steering to the right is defined by a negative steering angle and steering to the left is defined by a positive steering angle.

In figures 5 and 6, an example of abrupt steering behavior is given. Typical for this kind of behavior is a steering angle close to zero at first and from a certain moment, a much fluctuating steering angle. Also, the trajectory starts staying close to the middle line and at a certain place, deviates abruptly. In figure 10, two black, vertical lines indicate the time after which the participants start to steer to the right. These values are 1.55 seconds and 2.01 seconds. This shows that the participants take quite some time to start reacting. In figure 11, two black, vertical lines indicate the x-location at which the participants start to steer to the right. By comparing the steering angle in the bottom graph of figure 11 to the trajectory in the upper graph of figure 11, it shows that the steering reaction to evade occurs before this clearly shows on the trajectory.

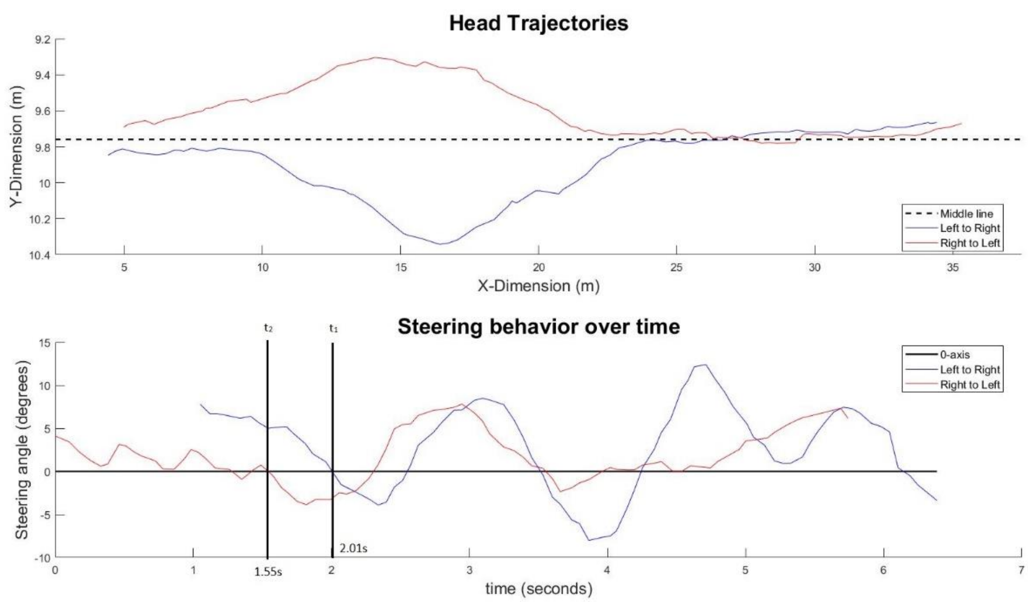

Figure 10 - Abrupt steering behavior over time

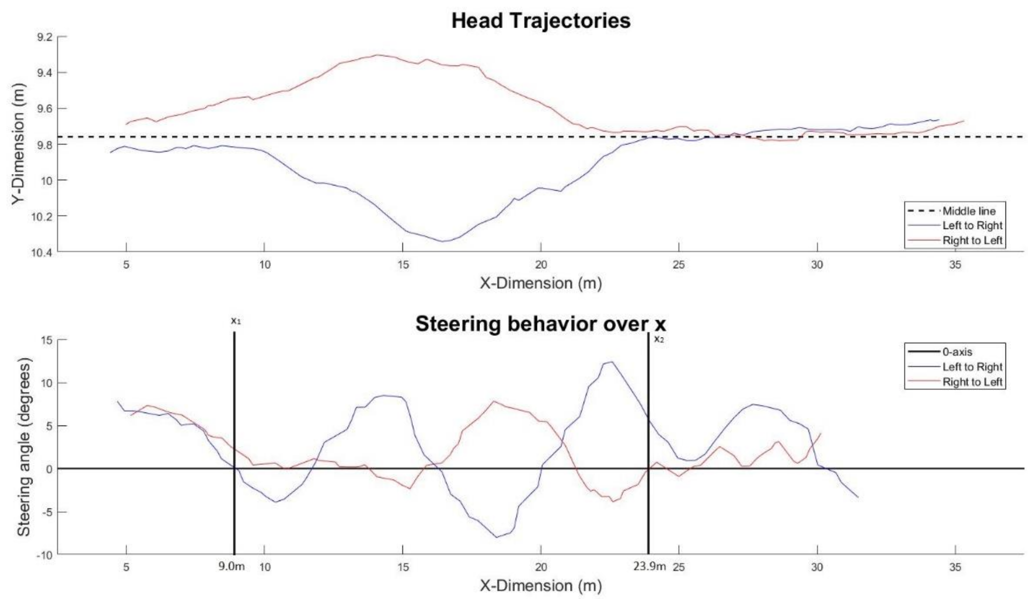

Figure 11 - Abrupt steering behavior over x

In figures 12 and 13, an example of abrupt steering behavior is given. Typical for this kind of behavior is a gradually moving steering angle and a trajectory which starts to gradually deviate from a certain moment. In figure 12, a black, vertical line indicates the time after which the participant, moving from left to right, starts to steer to the right. This value is 0.90 seconds. You can see that the participant, moving from right to left, is already steering to the right at the start. This shows that the participant reacted early. In figure 13, two black, vertical lines indicate the x-location at which the participants start to steer to the right. Again, it shows that the steering reaction to evade occurs before this clearly shows on the trajectory.

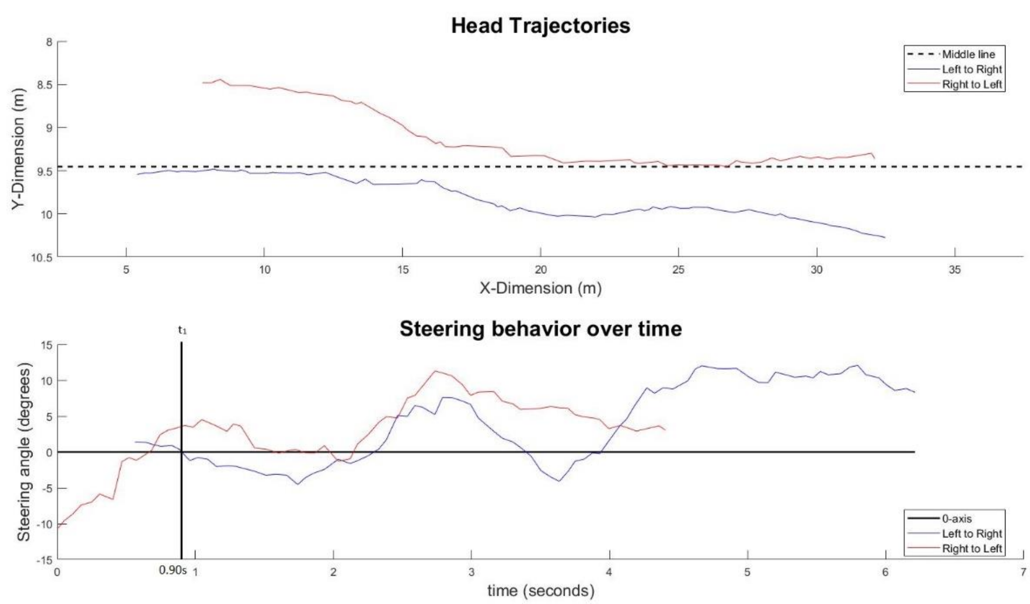

Figure 12 - Gradual steering behavior over time

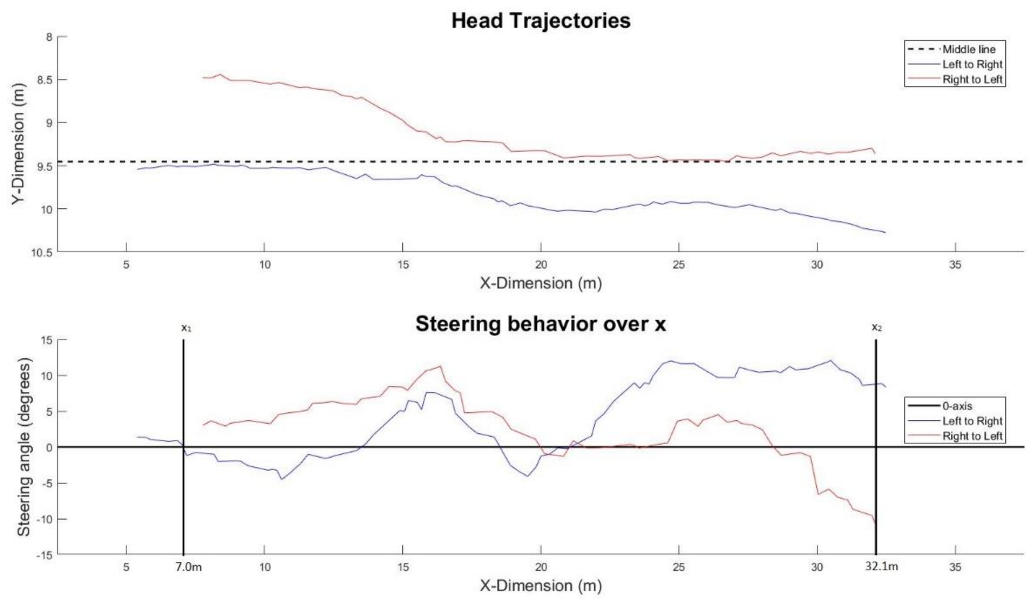

Figure 13 - Gradual steering behavior over x

Conclusively, steering reaction to evade occurs before this clearly shows on the trajectory. Furthermore, cyclists start to steer to evade almost immediately for gradual steering behavior and after some time, just before evading, for abrupt steering behavior.

Conclusion

From the results, the conclusions to answer the sub-questions can be drawn and after answering all sub-questions, the main question is answered. The answers to the first four sub-questions are mostly given in table 2, which is presented here again.

	1. Maximum lateral deviation	2.Interaction distance	3.x-difference maximum lateral deviations	4.x-movement after maximum lateral deviation	5.y-movement after maximum lateral deviation
5th percentile	0.30	0.61	-6.65	0	0
50th percentile	0.60	0.95	4.72	10.78	0.30
95th percentile	1.13	1.20	22.99	22.03	0.75

Furthermore, 11 percent of the participants continues evading from the middle line until the end and 4 percent follows a straight line after maximum lateral deviation. This suggest that for the 11 percent which continued evading, the observation area was not big enough to fully capture their evading behavior. The influence of gender on the evading behavior has also been found. It was concluded that women generally evade more than man and that the presence of a women is the dominant factor for the interaction distance, contrary to the presence of a male. The location and magnitude of deviation distances, which are presented in table 2, could be used in studies like that of Gould (Gould & Karner, 2009) or Zhao (Zhao et al., 2013) to determine single bicycle flow lane widths or passing lengths for bi-directional encounters. The 95th percentile for the interaction distance actually corresponds quite well to the 1.2 meter used by Gould (Gould & Karner, 2009) for a single bicycle flow lane width.

The role of steering behavior was analyzed by taking a look at the time and location where participants start to steer to evade. The steering reaction to evade occurs just before this clearly shows on the trajectory. Furthermore, cyclists start to steer to evade almost immediately for gradual steering behavior and after some time, just before evading, for abrupt steering behavior.

Conclusively, answering the main question, the quantitative behavior of cyclists is displayed in table 2. It presents the typical values (50th percentiles) and the boundaries, leaving out big outliers (5th and 95th percentile). Steering plays a significant role, since it was shown that it indicates the movement that the cyclist is about to make. This means that the steering angle is the determining factor for cyclists' interaction behavior in bidirectional encounters.

Limitations

Eleven percent of the participants were still evading when they crossed the line of the observation area, which means that for these 11 percent the evading behavior cannot be described fully. Subsequently, the quantitative results may differ somewhat from the actual case. Also, there is a small time offset between certain points used to determine the steering angle. The points should however have corresponding time values. This has a pretty big influence on the steering angle, making it significantly more inaccurate. This also makes any quantifications regarding the steering angle also inaccurate.

Recommendations

In future research it would be suggested to further inspect the steering behavior. For now only some qualitative results for the steering behavior were presented. The steering angles have already been computed, but an effective manner to analyze the inaccurate results should still be developed.

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