

Comparing different methods of crowdedness
calculation for cyclists at signalized
intersections

Lars Heijenrath

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Supervisors: Y. Yuan & R. Koster
Faculty of Civil Engineering and Geosciences

Summary

A lot of discomfort for cyclists can be prevented when more insights in the flow characteristics is gathered. Since little is known about these characteristics it is interesting to dive deeper in this subject. Since bicycle traffic keeps on growing in the Netherlands, it is important to obtain more insights into this mode of transport. Queueing and waiting during a trip is one of the most uncomfortable parts of travelling, so a lot can be gained by tackling this problem. This research is focused on cyclists waiting for a traffic light at signalized intersections. Motorized traffic is often used as a reference to compute different variables for bicycle traffic, although these modes of transport differ a lot. Motorized vehicles keep lanes, have a large turning circle and need more space between each other than cyclists.

There are different ways to calculate the crowdedness in an area, all leading to different results. These results can be used to create an insight of the crowdedness of cyclists in a certain area, but do not always provide useful information for further research, since no clear relation between other traffic variables can be made. This research is about finding the advantages and disadvantages of the different methods to calculate the crowdedness and study the relationships between the crowdedness and the queue discharge flow, as well as the shockwave speed. The main question in this report is: "*What are the different ways to calculate the crowdedness and how can these values be related to the discharge flow and the shock wave speed?*"

Different figures showed that some methods provide a better answer with respect to the relationship between the crowdedness and the other traffic variables.

The Voronoi diagram measure and the Harmonically Weighted Mean Distance measure fit this data set the best. It is hard to pick the best method for further research, since all methods have some pros and cons. For further research it might be good to check whether the methods which came out the best in this research are consistent for other data sets as well. When this is the case, a clear relationship between the crowdedness, the discharge flow and the shock wave speed can be established for cyclists at signalized intersections.

Contents

1	Introduction	4
2	Methodology	6
2.1	Different methods	6
2.1.1	Grid-Based measure	6
2.1.2	Range-Based measure	8
2.1.3	Voronoi diagram method	9
2.1.4	Exponentially Weighted Distance measure	10
2.1.5	Harmonically Weighted Mean Distance measure	12
2.1.6	Minimum Distance measure	14
2.2	Explanation of the set of data	15
3	Results	16
3.1	Crowdedness comparison	16
3.2	Results for Grid-Based method	16
3.3	Results for Range-Based method	20
3.4	Results for Voronoi diagram method	22
3.5	Results for Exponentially Weighted Distance measure	24
3.6	Results for Harmonically Weighted Mean Distance measure	26
3.7	Results for Minimum Distance measure	28
3.8	Overview of results	30
4	Discussion	31
5	Conclusion	32
A	Appendices	33
A.1	First Appendix	33
A.2	Second Appendix	33
A.3	Third Appendix	34
A.4	Fourth Appendix	37
A.5	Fifth Appendix	38
A.6	Sixth Appendix	40
A.7	Seventh Appendix	41
A.8	Eighth Appendix	42

1 Introduction

Over the last years, the distance traveled with bikes has increased in the Netherlands. Furthermore, the Dutch have the highest bicycle/capita ratio[1]. Both these facts indicate this way of traveling is used a lot among the Dutch. However, since so many people choose to take the bike to their destination, it gets crowded at the cycling paths. This causes discomfort for the cyclists. To minimize this discomfort, it is useful to gather more insight into the characteristics of bicycle flow. In order to optimize the discharge flow of a group of cyclists, it is important to gather information about the number of cyclists in the queue and the spatial distribution [2]. To obtain more insight into the crowdedness, the data set which has also been used in the paper of Goñi-Ros et al. [3], will be used. Linear relationship between jam crowdedness, shock wave speed and discharge flow were established as a result of this report. The term 'density' is not used in this report since 'density' is measured in cyclists per meter squared. Instead crowdedness is used. This term is more extensive and can be used for all the different methods. The results can be used in future research to give a better prediction of the discharge flow and shockwave speed given the crowdedness of a group of cyclists. This data is collected from a bicycle lane in Amsterdam using cameras. The *discharge flow* is defined as the average number of cyclists that pass the stop line per unit of time. The *shock wave speed* is the speed at which the shock wave moves upstream [3].

From earlier research of Duives, Daamen and Hoogendoorn [2] it became clear that for pedestrians the crowdedness influences the discharge flow. However, many ways are used to calculate the crowdedness in this research, and only a few of them could be related to this crowdedness and the discharge flow directly.

The main question to be answered in this research will be: "*What are the different ways to calculate the crowdedness and how can these values be related to the discharge flow and the shock wave speed?*" The sub-questions are the following.

- How to quantify the crowdedness of the cyclists?
- Is there a correlation between the discharge flow and the crowdedness?
- Is there a correlation between the shockwave speed and the crowdedness?

General traffic management authorities are the most important stakeholder here, since the obtained findings provide improved insights in the cyclist travel flow. Since little is known about the characteristics of bicycle flow (in contrast to other transportation modes) it is interesting to come up with new results. This is one of the main motivations for doing this research. First, the methodology of this research will be explained. This is done in chapter 2. The data set which is used in this research will be explained in this chapter as well. Beside the data set, an explanation of all the different methods for crowdedness calculation will be provided. In chapter 3 the results extracted from the data set will be shown. Combined with different figures, the difference between the methods will be made clear. In chapter 4 the limitations of this research will be discussed. Finally, in chapter 5 the answer to the main question will be given and the conclusion of the research will be drawn.

2 Methodology

2.1 Different methods

The crowdedness of cyclists is usually measured as the cyclists per meter squared. However, different methods lead to different expressions for the crowdedness. In the figures drawn below, the different methods to calculate the crowdedness are presented. Every black dot represents a single cyclist in the queue. Six methods for crowdedness calculation are tested. The selection of methods is based on the methods that are used in the paper of Duives et al. [2]. These methods were capable of calculating the level of crowdedness across a two-dimensional area given the location of the different cyclists at a time moment. For this research, the jam crowdedness will be compared to other traffic variables. This is defined as the crowdedness at the moment people are queueing and standing still.

2.1.1 Grid-Based measure

For this method an orderly grid has to be placed over the bicycle lane. By calculating the number of cyclists in a grid cell (counting) it becomes possible to calculate the crowdedness in that part of the grid. This first method was founded by Fruin [4] in 1971, to estimate the crowdedness for pedestrian traffic. For the calculations and results, no adjustments have to be made for the transition from pedestrians to cyclists. Lower values will be expected compared to the pedestrians, since the bikes of the cyclists cover a larger area than a single pedestrian and less space will be available for the other cyclists.

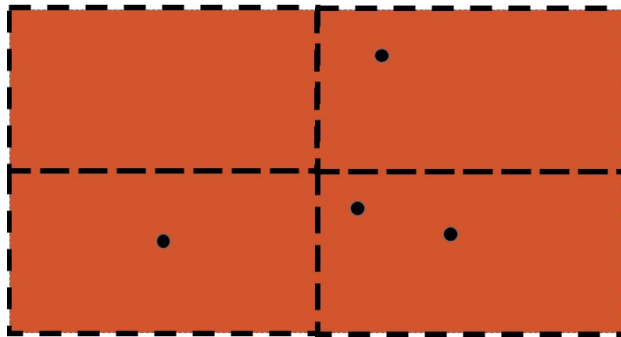


Figure 1: Grid-base overview

The crowdedness can now be calculated in each cell by dividing the number of cyclists in each cell by its area.

This can be mathematically formulated as follows:

$$\vec{x}_c(t) \in X_c \Rightarrow \rho(c, t) \quad (1)$$

$$\rho(c, t) = \frac{\sum_d n_d(t)}{A_c} \quad (2)$$

$$n_d(t) = \begin{cases} 1, & \text{if } \vec{x}_d \in X_c \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

where $\vec{x}_c(t)$ and $\vec{x}_d(t)$ represent the coordinates of the cyclist c for which the crowdedness is calculated and the cyclist d present within the infrastructure at time t respectively. X_c represents the coordinates within the grid cell c and A_c represents the area of cell c .

Finally, the average crowdedness of the different cells will be taken into account for further calculations. A distinction will be made in the figures. One of the submethods will not take cells into account which are not filled with any cyclists. This will lead to higher values for the crowdedness. The other submethod does, although this might lead to an underestimation of the jam crowdedness.

2.1.2 Range-Based measure

The range-based method calculates the crowdedness within a circle around a cyclist with radius r . A visualisation is presented in figure 2.

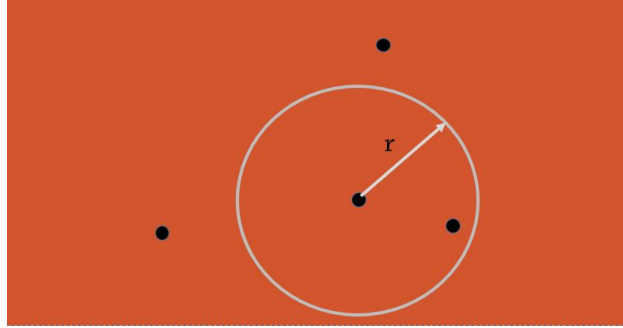


Figure 2: Range-base overview

When the virtual circle is drawn around a cyclist, the number of cyclists in this circle is counted. Subsequently, this number will be divided by the area of the circle ($\pi * radius^2$). This is done for all the cyclists in line. The average of all the cyclists in line is taken into account for further calculations and the correlation with the other traffic variables.

This method can be mathematically formulated as follows:

$$\rho(\vec{x}_c, t) = \frac{\sum_d n_d(t)}{A_c} \quad (4)$$

where

$$n_d(t) = \begin{cases} 1, & \text{if } |\vec{x}_d(t) - \vec{x}_c(t)| < r \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

This method is used to calculate the crowdedness around the location of the cyclist. The average value is taken into account for the plots.

2.1.3 Voronoi diagram method

Another method which has been used on pedestrian crowdedness as well, was proposed by Steffen et al. [5]. The method calculates the crowdedness based on space measurements. The method creates a cell around a datapoint in which all the locations in the cell are closer to the cyclist c than to any other cyclist.

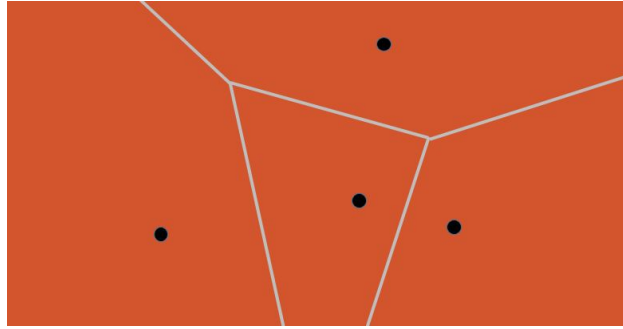


Figure 3: Voronoi overview

The method can be mathematically formulated as follows:

$$\rho(\vec{x}_c, t) = \frac{1}{A_c} \quad (6)$$

The drawn polygons do not enclose at the boundaries of the diagram. This leads to infinite values for A_p , which would imply that the crowdedness in this cell would be 0. However, the `VoronoiLimit` function in Matlab takes care of this problem. See Appendix A.5 for the implementation of the `VoronoiLimit` function in the code. It generates virtual boundaries to prevent infinite areas.

2.1.4 Exponentially Weighted Distance measure

This method uses the location of the cyclist in the crowdedness estimation. A Gaussian distance-dependent weight function is used in the measurement. (Eq. 7)

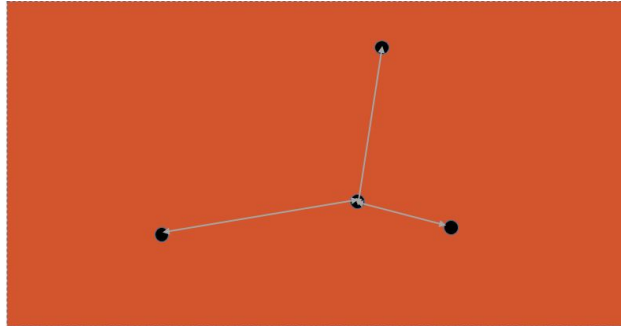


Figure 4: EWD overview

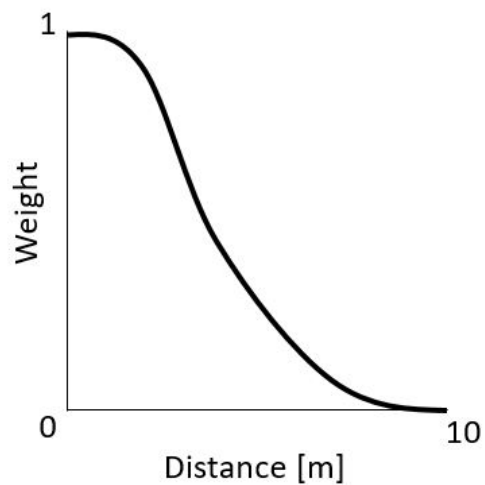


Figure 5: weight function for EWD

The exponentially weight measurement allows for a continuous estimation of the experienced crowdedness. Furthermore, this function allows the method to make a clear distinction between cyclists that are further away

and cyclists that are close to the referenced cyclist. Figure 4 provides an visual representation. This distinction is integrated in formula 7 by constant β_1 .

This method can be mathematically formulated as follows:

$$\rho(\vec{x}_c, t) = \frac{\beta_1}{\pi} \sum_d \exp[-\beta_2 |\vec{x}_d(t) - \vec{x}_c(t)|^2] \quad (7)$$

The smaller β_1 is chosen, the more local the outcome for the crowdedness will become. Note that all the detected cyclists within the radius of influence are accounted for less that one person. This results in the fact that for uncrowded situations this estimation will be lower than the real crowdedness. This results in an underestimation. Constant β_2 is used to adapt to this underestimation. In more crowded situations this method works better.

2.1.5 Harmonically Weighted Mean Distance measure

The Harmonically Weighted Mean Distance measure calculates the crowdedness at the current location of the cyclist. The method calculates the average distance between cyclist c and all the other cyclists d at time instance t within the infrastructure. Figures 6 and 7 provide an visual representation of the method.

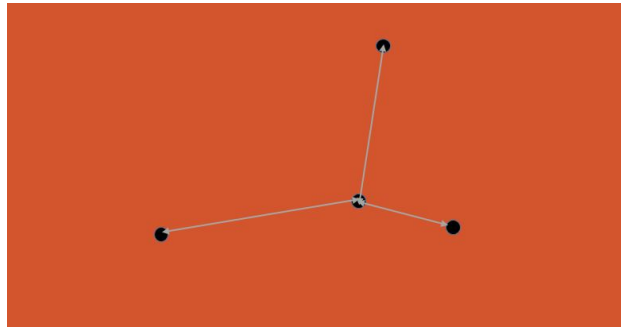


Figure 6: HWMD overview

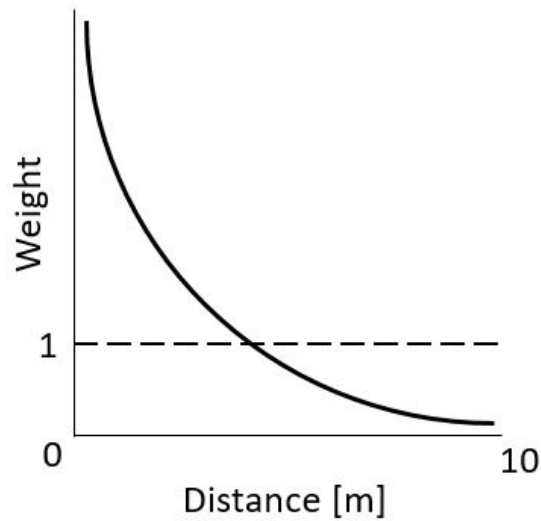


Figure 7: weight function for HWMD

In contrast to the earlier described methods the units of this measure are

meters. A high ρ would suggest that the crowdedness is high, so the distance between cyclists is small. This method can be mathematically formulated as follows:

$$\rho(\vec{x}_c, t) = \sum_d \frac{1}{|\vec{x}_d(t) - \vec{x}_c(t)|} \quad \forall d, c \in C | d \neq c \quad (8)$$

The main difference between the Harmonically Weighted Mean Distance measure (HWMD) and the Exponentially Weighted Distance measure (EWD) is that the first mentioned method looks at the inverse of the distance headway only, so no extra estimations or calibrations of parameters have to be made. The results do not need too much computational effort since the only variable is the distance to other cyclists.

2.1.6 Minimum Distance measure

Taking a look at the behaviour of pedestrians, studies of Moussaïd et al. [6] and Paris et al. [7] suggest that the decisions of pedestrians might be taken solely by the distance to the closest other pedestrian. These studies will be tested on the set of cyclists as well. The crowdedness in this method is expressed as the distance to the closest other cyclist. Due to the size of the human body and the size of a bicycle, the minimal ρ will be around 0.50 m.

This method can be mathematically formulated as follows:

$$\rho(\vec{x}_c, t) = \min(|\vec{x}_d(t) - \vec{x}_c(t)|) \quad \forall d, c \in C | d \neq c \quad (9)$$

The method is visualized in figure 8.

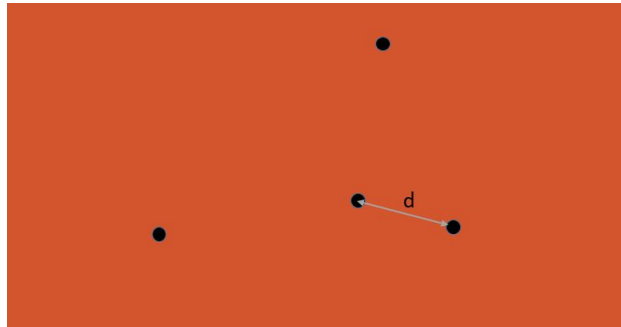


Figure 8: Minimal Distance overview

2.2 Explanation of the set of data

The data contains 59 discharge processes for different groups of cyclists at the same signalized intersection in Amsterdam. Two out of this 59 are not used in further calculations since something went wrong with these measurements. The data set contains the positions of different cyclists at different time moments. This positions were extracted from pictures taken by two cameras; one facing in the direction of the bicycle flow and the other in opposite direction. A short Matlab code (see appendix A.1) provides a good overview for the different queues. For example figure 9 shows one of these queues with the x and y coordinates of all the cyclists. Different variables such as the shock wave speed and the discharge flow have been calculated in Matlab before the start of this research.

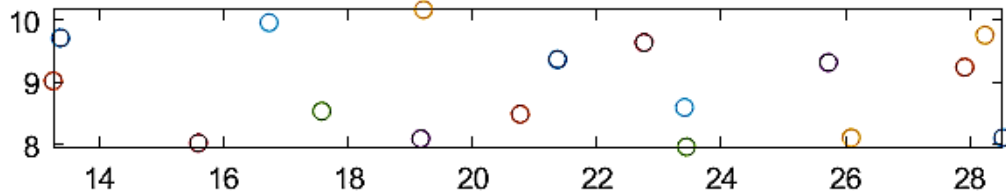


Figure 9: Visualisation of one of the queues

3 Results

3.1 Crowdedness comparison

The same data that is used in [3] will be used in this report. The used data contains 57 discharging processes of bicycle flow. All these periods were measured at the same signalized intersection in Amsterdam. In this report, mainly the spacial distribution will be used. To get quantitative results for the crowdedness measurements, Matlab will be used. Matlab is able to compute the desired outcome which will show the different densities. For the grid based method, the range based method, the exponentially weighted distance method, the harmonically weighted mean distance method and the minimum distance method different new functions were written in Matlab. Those are provided in the appendix. For the Voronoi diagram method some existing methods were used. Combined with different methods to calculate crowdedness in a certain area, all results will contain the exact values. When all the results of the different methods have been calculated in Matlab, an overview of the different characteristics will be provided, both qualitative as quantitative. All the methods will be tested and compared on different characteristics, which will indicate the method which describes the crowdedness the best for the used data set. This crowdedness will then be related to the other variables, the discharge flow and the shock wave speed. These results show the variety of methods and provide an overview of the different characteristics. The first part of the code for every method is the same. This is added in appendix A.2.

3.2 Results for Grid-Based method

The first method which is used to calculate the crowdedness is the grid-based method. Figure 10 shows the results obtained from the data set. The Matlab code is added in appendix A.3. The location of all the cyclists is obtained and this area is divided in six cells with an equal area. In figure 10 a distinction between two submethods is shown. One of them ignores crowdedness values that equal 0, while the other one does not. This influences the jam crowdedness. The range of the crowdedness is between 0.15 and 0.44 cyclists per m^2 for the submethod which includes the 0 values, and between 0.22 and 0.44 cyclists per m^2 for the submethod which ignores the 0 values.

Next to the histogram the following figures show the correlation between

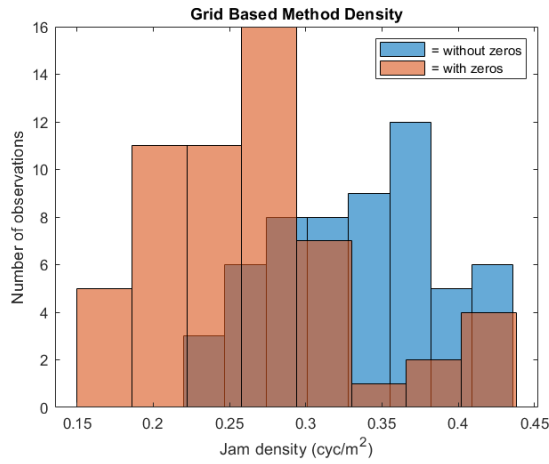


Figure 10: Grid Based results in a histogram

the jam crowdedness and the shock wave speed. In figure 11, the cells with zero cyclists in it are taking in to account. In figure 12 these cells are ignored in the calculation.

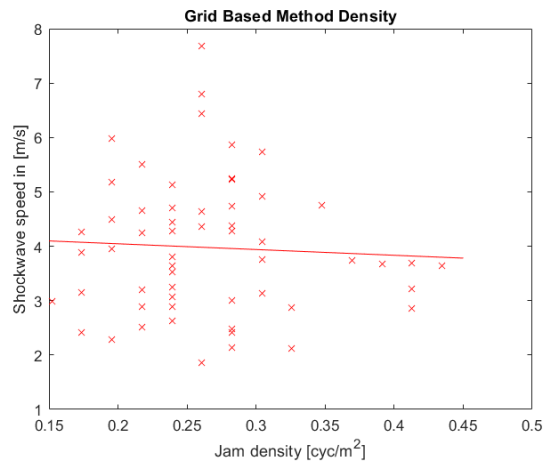


Figure 11: GB results vs shock wave speed

Besides the shock wave speed, the crowdedness is plotted against the discharge flow. Again, a distinction between two submethods is used. In figure 13 the cells without any cyclist in it are taking in to account. In figure 14 those cells are left out of the calculation. For both submethods it is

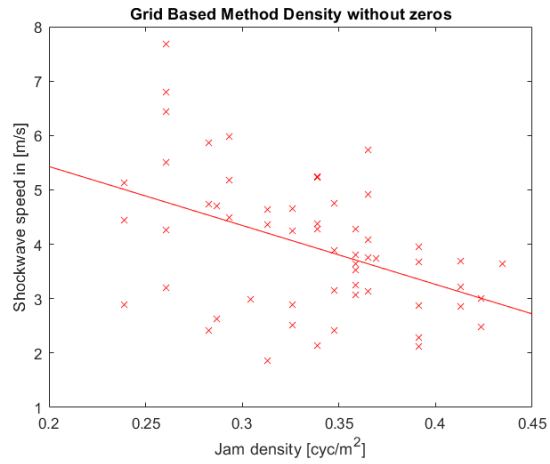


Figure 12: GB results vs shock wave speed

clear to see that when the crowdedness increases the discharge flow increases as well. For the shock wave speed it is the other way around. When the crowdedness increases the shock wave speed decreases. The fitted line for the data without empty cells is steeper than the line for the data with all cells taken into account.

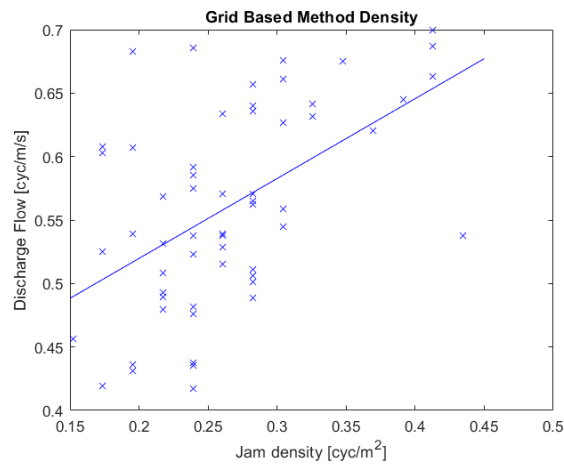


Figure 13: GB results vs discharge flow

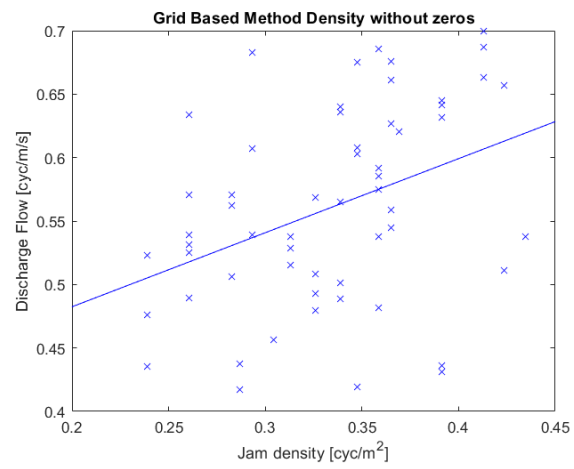


Figure 14: GB results vs discharge flow

3.3 Results for Range-Based method

The second method is the range based method. Figure 15 shows the results which are obtained. The Matlab code is added in appendix A.4. The values for the crowdedness are between 0.30 and 0.55 cyclists per m^2 .

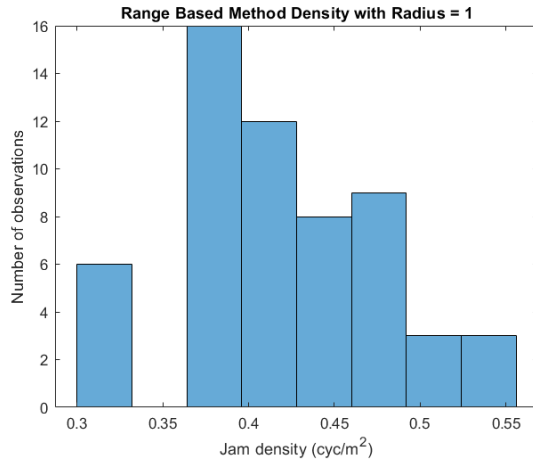


Figure 15: Range Based results in a histogram

As with the previous method the histogram doesn't show all the information gathered from Matlab. In figure 16 the relation with the shock wave speed is presented. Figure 17 shows the correlation between the discharge flow and the crowdedness. Again, a positive correlation between discharge flow and crowdedness is obtained when using this method.

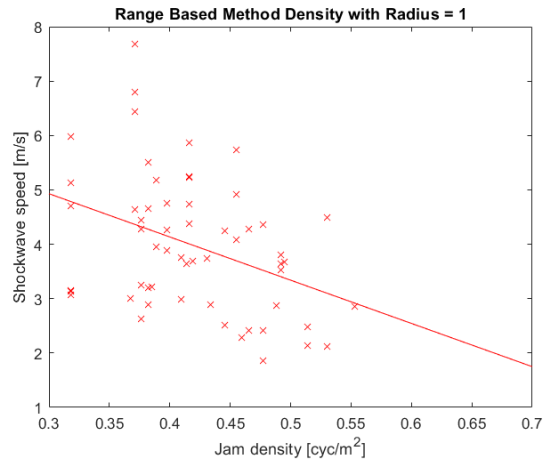


Figure 16: Range Based results vs shock wave speed

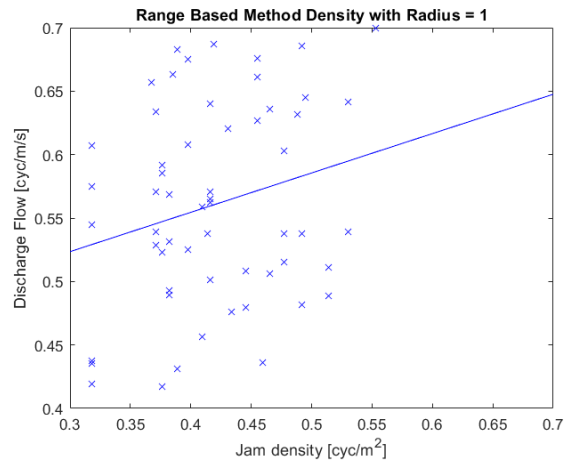


Figure 17: Range Based results vs discharge flow

3.4 Results for Voronoi diagram method

The Voronoi diagram measure took more time since the calculation is more complex. First, Matlab has to generate 57 different figures with different cells in it. After that the areas of all the polygons have to be calculated. Figure 18 shows the histogram with the results. The code is added in appendix A.5. For the Voronoi diagram method it is a bit harder to gather useful results. Since a mean value of all the cell areas will result in the same value as the division of the number of cyclists by the area they are standing in, this is not useful. Plotting the area of the smallest cell for all the processes neither will provide a good overview of all the data since one pair of cyclists can influence the final results from one process. Instead, the area of all cells are plotted against the calculated discharge flow and shock wave speed. The values for the crowdedness mainly varies between 0 and 5 per m^2 .

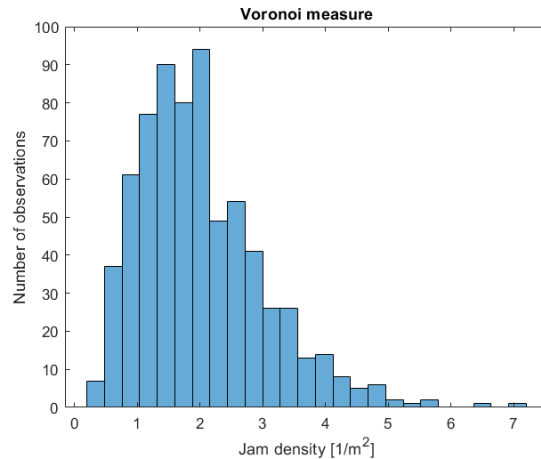


Figure 18: Voronoi Diagram results in a histogram

Subsequently, crowdedness is plotted against the shock wave speed. See figure 19. When the area of the cells become larger the shock wave speed increases. This describes the correct relation between those variables.

Finally, the crowdedness is plotted against the discharge flow. The results are plotted in figure 20. When the bike lane has less cyclists the discharge flow will be lower. The fitted line shows the correct relation between those variables.

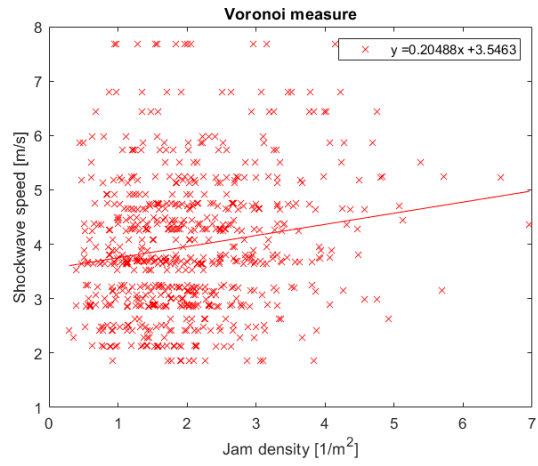


Figure 19: Voronoi Diagram results vs shock wave speed

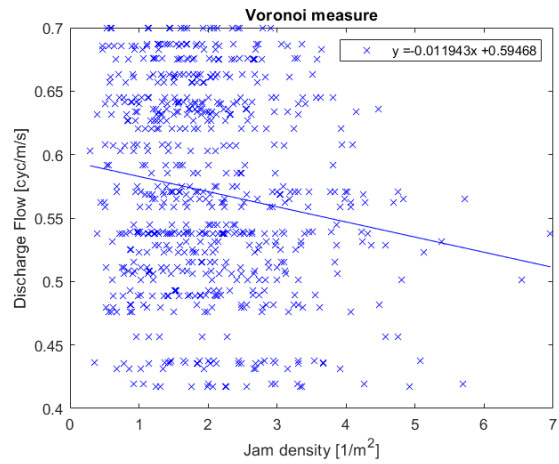


Figure 20: Voronoi Diagram results vs discharge flow

3.5 Results for Exponentially Weighted Distance measure

The next method is the Exponentially weighted distance method. Figure 21 shows the histogram with the obtained results. The Matlab code is added in appendix A.6. The values for the crowdedness are between 0.34 and 0.54 cyclists per m^2 .

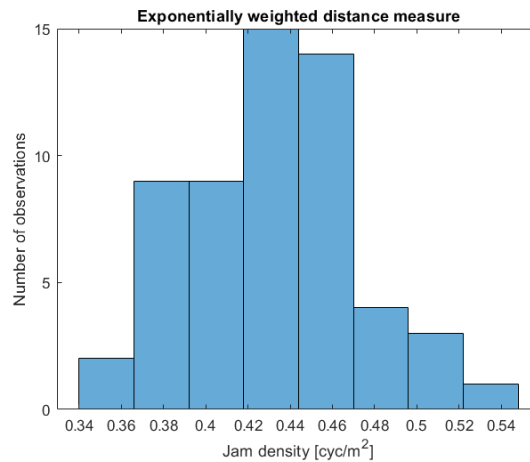


Figure 21: Exponentially Weighted Distance measure results in a histogram

In figure 22 the correlation with the shock wave speed is shown. From this figure it is possible to see that when the value for the crowdedness increases, the value for the shock wave speed gets lower.

Finally, figure 23 shows the positive correlation between the discharge flow and the crowdedness.

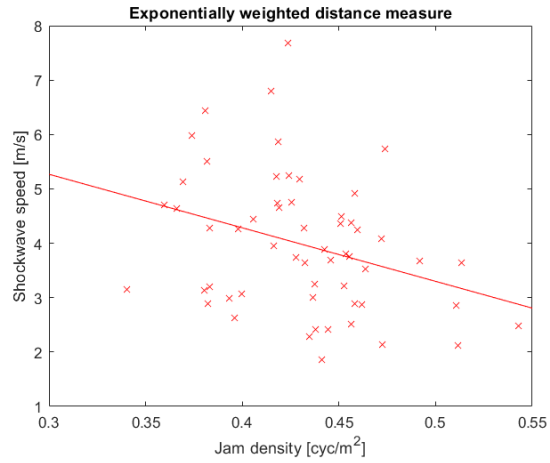


Figure 22: Exponentially Weighted Distance measure results vs shock wave speed

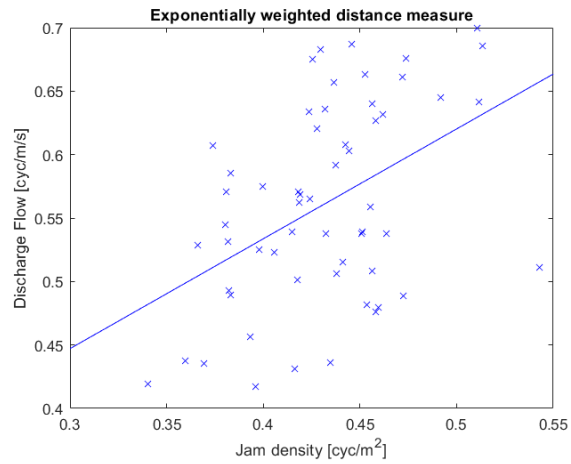


Figure 23: Exponentially Weighted Distance measure results vs discharge flow

3.6 Results for Harmonically Weighted Mean Distance measure

The next method is the Harmonically Weighted Mean Distance method. Figure 24 shows the histogram with the results. The code which is used for this method is added in appendix A.7. The values of the crowdedness are between 2.1 and 5.2 *m*.

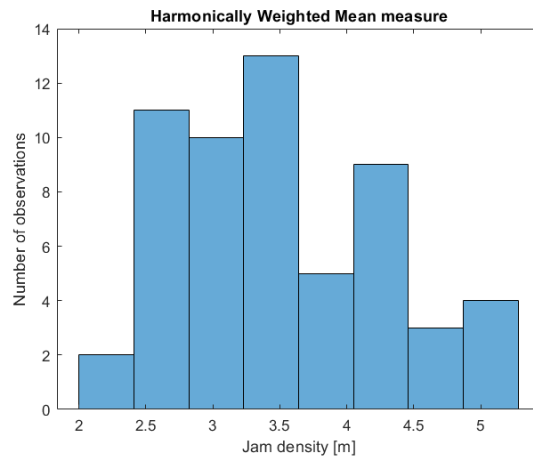


Figure 24: Harmonically Weighted Mean Distance measure results in a histogram

In figure 25 the correlation between the crowdedness and the shock wave speed is shown.

Subsequently, the correlation between the crowdedness and the discharge flow is plotted in figure 26.

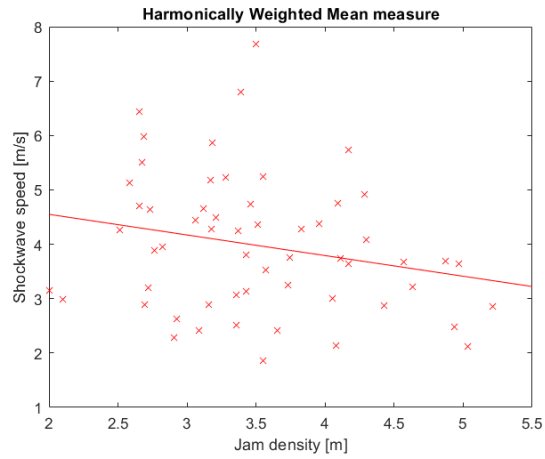


Figure 25: Harmonically Weighted Mean Distance measure results vs shock wave speed

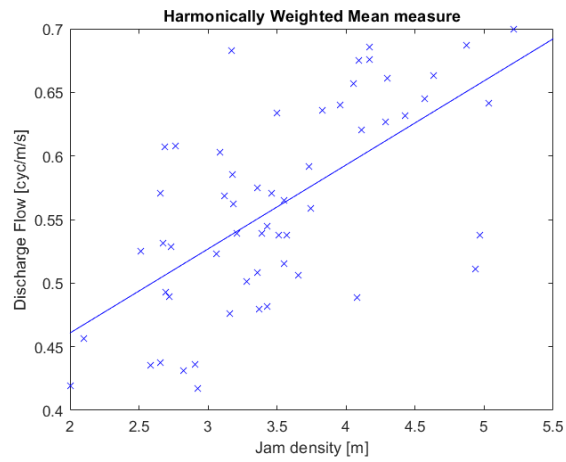


Figure 26: Harmonically Weighted Mean Distance measure results vs discharge flow

3.7 Results for Minimum Distance measure

The final method is the Minimum Distance method. It provides an overview to the distance of the closest other cyclist, seen from cyclist c . Figure 27 shows the histogram plot. The code which is used to gather this result is added in appendix A.8. The values of the crowdedness are between 0.5 and 1.5 m .

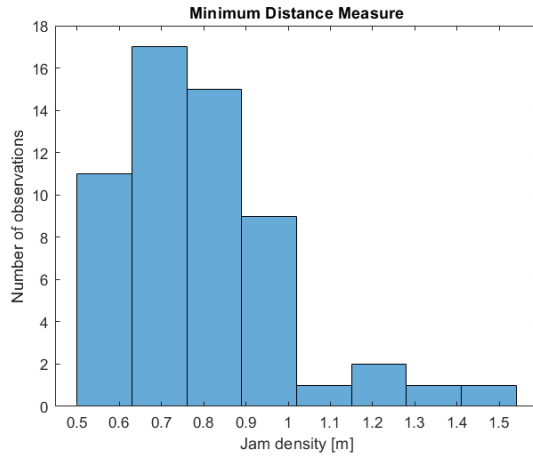


Figure 27: Minimum Distance measure results in a histogram

In figure 28 the correlation between the crowdedness in metres and the shock wave speed is shown.

Finally, figure 29 shows the negative correlation between the crowdedness and the discharge flow. However, when the value for the crowdedness becomes larger, the distance (minimum) distance between the cyclists becomes larger, so less cyclists will cross the stop line in a (short) period of time.

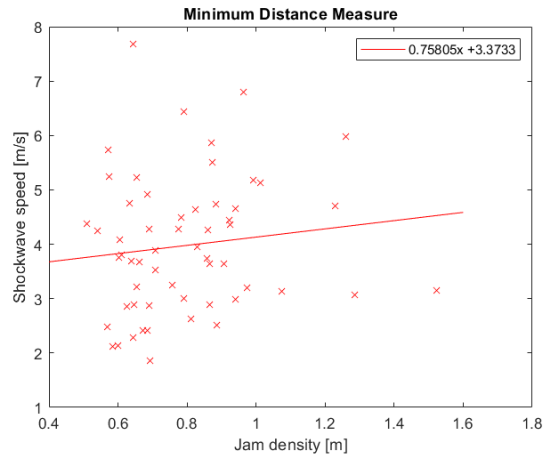


Figure 28: Minimum Distance measure vs shock wave speed

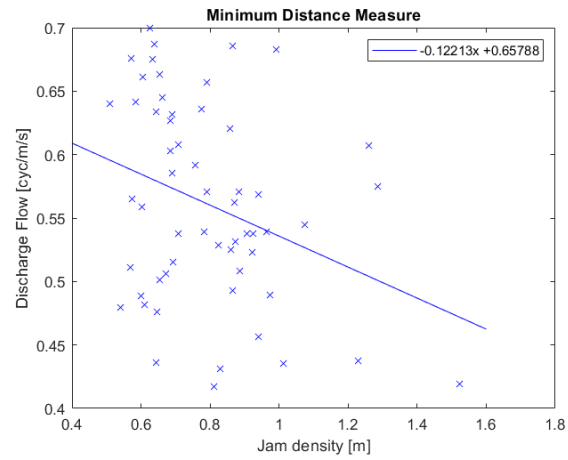


Figure 29: Minimum Distance measure vs discharge flow

3.8 Overview of results

Merging all the results leads to the the overview provided in Table 1. For every method the assumptions, correlation with the shock wave speed, correlation with the discharge flow and the crowdedness range have been are in this table. It is clear to see that all methods correlate with both the shock wave speed and the discharge flow. Some might be positively corelated to those variables while other are negatively correlated, but this is just a matter of unity of the measurement.

Table 1: Overview of the results

Measure	Units	Assumptions	SW speed* correlation	DF** correlation	Crowdedness range
Grid-based	Cycl/m ²	Size of the cell, location of the cell	Yes (negative)	Yes (positive)	0.15 - 0.45
Range-based	Cycl/m ²	Radius around cyclist	Yes (negative)	Yes (positive)	0.30 - 0.55
Voronoi Diagram	1/m ²	None	Yes (positive)	Yes (negative)	0.00 - 5.00
Exponentially Weighted Distance	Cycl/m ²	Radius of influence, weight of distances	Yes (negative)	Yes (positive)	0.34 - 0.54
Harmonically Weighted Mean Distance	m	None	Yes (negative)	Yes (positive)	2.00 - 5.20
Minimum Distance	m	None	Yes (positive)	Yes (negative)	0.50 - 1.50

* = Shock Wave speed, ** = Discharge Flow

4 Discussion

All methods are tested and came up with different results. And although all of them pass the fact that they correlate on the right way with the shock wave speed and the discharge flow, some of them still come with limitations. The grid based measure is limited to the fact that the size of the cell and the location of the cell influence the outcome of the method. The size of the cells have to be limited but there is no "best" value for its size.

The range based measure has some limitations as well. First of all, the radius influences the obtained values for the crowdedness. Higher values of the radius seem to result in lower values for the crowdedness. What is also happening with the range based measure is that a part of the area of the virtually drawn circles is outside of the borders of the bike path. And since there are no cyclists over there, the calculation results in an underestimation and is not very representative.

The calculation time for the voronoi diagram method is longer than all the other methods and will become even longer when the data set becomes bigger. This might result in long waiting times before getting any results which is not ideal.

The exponentially weighted distance method does not have these problems. Although the radius of influence and the weight of the distances is variable. The harmonically weighted mean distance does come up with good results for this research but will be less useful when it is used in situations where the cyclists are moving.

Finally, the minimum distance measure is left. No assumptions had to be made. The average minimum distance is plotted for every discharging process, since individual minimum distances didn't lead to (significantly) different results.

Besides the stated downsides of the methods themselves, the data set itself is not large enough to be representative. The answer to the research questions will be based on this single data set.

The Matlab code could be used for other datasets as well when those data sets provide x and y coordinates in the same format.

5 Conclusion

The main goal of this report is to provide an overview of the different methods to calculate crowdedness for cyclists at signalized intersections and to compare those methods to come up with a specific method which describes the correlation between the different traffic variables (discharge flow and shock wave speed) the best for the given data set. With these relations it is possible to reduce the delay at signalized intersections by optimizing the way cyclists stand in line for the traffic light and gather more insights in the behaviour of the speed of the discharge process. In section 4 the pros and cons of the different methods are highlighted. The Harmonically Weighted Mean Distance measure and the Voronoi Diagram measure fit the data the best. Both methods provide a clear correlation between the measured crowdedness and the other traffic variables. The Voronoi diagram method needs some extra computational time but works for every arbitrary data set (provided that the x y positions could be read easily from the provided data set) without any assumptions. However, when the data set becomes larger it might be better to come up with an alternative method. The simplicity of the HWMD measure and the fact that no assumptions have to be made ensure that this method is very useful for this data set.

The minimum distance measure would be a good alternative for those two since no assumptions have to be made before the computation as well. The exponentially weighted distance method gives good results when β_1 and β_2 are chosen correctly. The range based measure and the grid based measure are too dependent on the pre-made assumptions.

This research has shown that all discussed methods have pros and cons, so it is hard to pick the best method in all situations. However, this outcome is a step in the right direction for further research.

A Appendices

A.1 First Appendix

```
for j = [1:length(x_ini)]
    plot(x_ini(j), y_ini(j), 'o'); hold on
    figure(i);
    h = vline(28.7);
    axis([9 30 7.5 10.5])
    daspect([1 1 1])
    axis([min(x_ini) max(x_ini) min(y_ini) max(y_ini)])
end
```

A.2 Second Appendix

```
clear; close all; clc;

filename = [{'12-45-16_1'},...
           {'13-00-18_1'},{'13-00-18_2'},{'13-00-18_3'}...
           {'13-15-20_1'},{'13-15-20_2'},{'13-15-20_3'},...
           {'13-30-22_1'},{'13-30-22_2'}...
           {'13-45-23_1'},{'13-45-23_2'},...
           {'14-00-24_1'},{'14-00-24_2'},{'14-00-24_3'}...
           {'14-15-26_1'},{'14-15-26_2'},...
           {'14-30-27_1'},...
           {'14-45-29_1'},{'14-45-29_2'},...
           {'15-00-30_1'},{'15-00-30_2'},...
           {'15-15-32_1'},{'15-15-32_2'},...
           {'15-45-35_1'},{'15-45-35_2'},...
           {'16-00-37_1'},...
           {'16-15-39_1'},...
           {'16-30-41_1'},{'16-30-41_2'},...
           {'16-45-42_1'},{'16-45-42_2'},{'16-45-42_3'},{'16-45-42_4'},...
           {'17-00-44_1'},{'17-00-44_2'},{'17-00-44_3'},{'17-00-44_4'},...
           {'17-15-45_1'},{'17-15-45_2'},{'17-15-45_3'},{'17-15-45_4'},{'17-15-45_5'},...
           {'17-30-47_1'},{'17-30-47_2'},{'17-30-47_3'},{'17-30-47_4'},{'17-30-47_5'}...
           {'17-45-48_1'},{'17-45-48_2'},{'17-45-48_3'},{'17-45-48_4'},...
           {'18-15-52_1'},...
           {'18-30-54_1'},{'18-30-54_2'},{'18-30-54_3'},{'18-30-54_4'},{'18-30-54_5'},...
           {'19-00-58_1'},{'19-00-58_2'}];

fnam_length = length(filename);

% files = dir([pwd filesep 'Trajectory_data_for_analysis_IP_PT_NP' filesep 'Traj_2016-06-02_*.mat']);
% filename = [pwd filesep files(i).name];

% Extract data

all_initpos_Npred_TT_pre = [];

load ('SWspeed.mat') % SWspeed_final (method 1)

load ('ShockwaveSpeed.mat') % SWspeed (method 0)

load ('EdieQKV.mat')

% w = SWspeed([1:18 21:fnam_length],1);
% w = SWspeed(:,1);

width = 2; % The width of the bicycle lane

Kj = [];
Q = [];
Kc = [];
w = [];

Kj1 = [];
Q1 = [];
Kc1 = [];
w1 = [];

Qedie = [];
Kedie = [];
```

```

Vedie = [];

for i = [1:18 21:fnam_length] %exclude period 19 20 % 1 : fnam_length [1:18 21:fnam_length] [1:18 21 23 25:fnam_length]

    load([pwd filesep 'Trajectory_data_for_analysis_IP_PT_NP_DH' filesep 'Traj_2016-06-02_' filename{i} '.mat']);

    if i == 3 || i == 48 || i == 55
        passing_times(2) = [];
        pos_init(2,:) = [];
        %traj(2) = [];
    elseif i == 40
        passing_times(12) = [];
        pos_init(12,:) = [];
        %traj(12) = [];
    end

    NoNaN = length (find(isnan(passing_times)));
    [PT,I] = sort(passing_times((NaN+1):end),'ascend');
    x_ini = pos_init(:,1);
    y_ini = pos_init(:,2);
    index = find(x_ini<xSL);
    x_ini = x_ini(index);
    y_ini = y_ini(index);

    N = length(passing_times);
    N1 = length(PT);

    t = max(passing_times)-greenPhaseStartTime;
    t1 = max(PT) - min(PT);

    % xSL = 28.45;
    L = xSL - min(pos_init(:,1));
    L1 = max(x_ini) - min(x_ini);
    B1 = max(y_ini) - min(y_ini);

    Q = [Q; (N/t)/width];
    Kj = [Kj; (N/L)/width];
    Kc = [Kc; Kcri/width];
    w = [w;SWSpeed(i,1)];

    Q1 = [Q1; ((N1-1)/t1)/width];
    Kj1 = [Kj1; ((N1-1)/L1)/width];

    Kc1 = [Kc1; Kcri1/width];

    w1 = [w1;SWSpeed_final(i)];

    Qedie = [Qedie; QE(i)/width];
    Kedie = [Kedie; KE(i)/width];
    Vedie = [Vedie; VE(i)];

end

folderName = ([pwd filesep 'RelationPlots' filesep]);

```

A.3 Third Appendix

```

counter1 = [];
counter2 = [];
counter3 = [];
counter4 = [];
counter5 = [];
counter6 = [];
y_min = [];
y_max = [];
x_min = [];
x_max = [];
for i = [1:18 21:fnam_length]
    load([pwd filesep 'Trajectory_data_for_analysis_IP_PT_NP_DH' filesep 'Traj_2016-06-02_' filename{i} '.mat']);
    x_ini = pos_init(:,1);
    %x_ini = x_ini(x_ini<xSL);
    y_ini = pos_init(:,2);
    index = find(x_ini<xSL);
    x_ini = x_ini(index);
    y_ini = y_ini(index);
    y_min(i) = min(y_ini);

```

```

y_max(i) = max(y_ini);
x_min(i) = min(x_ini);
x_max(i) = max(x_ini);
if i == 3 || i == 48 || i == 55
    passing_times(2) = [];
    pos_init(2,:) = [];
    %traj(2) = [];
elseif i == 40
    passing_times(12) = [];
    pos_init(12,:) = [];
    %traj(12) = [];
end
end
y_min = min(y_min([1:18 21:59]));
y_max = max(y_max([1:18 21:59]));
y_middle = (y_min + y_max)/2;
x_min = min(x_min([1:18 21:59]));
x_max = max(x_max([1:18 21:59]));
x_first = (x_max - x_min) / 3 + x_min;
x_second = 2*(x_max - x_min) / 3 + x_min;
x_third = x_max;
cell_area = (x_first - x_min)*(y_middle - y_min);

%histogram(counter1,16); hold on;

for i = [1:18 21:fnam_length]
    load([pwd filesep 'Trajectory_data_for_analysis_IP_PT_NP_DH' filesep 'Traj_2016-06-02_' filename{i} '.mat']);
    x_ini = pos_init(:,1);
    %x_ini = x_ini(x_ini<xSL);
    y_ini = pos_init(:,2);
    index = find(x_ini<xSL);
    x_ini = x_ini(index);
    y_ini = y_ini(index);
    counter1(i) = 0;
    counter2(i) = 0;
    counter3(i) = 0;
    counter4(i) = 0;
    counter5(i) = 0;
    counter6(i) = 0;
    if i == 3 || i == 48 || i == 55
        passing_times(2) = [];
        pos_init(2,:) = [];
        %traj(2) = [];
    elseif i == 40
        passing_times(12) = [];
        pos_init(12,:) = [];
        %traj(12) = [];
    end
    end
    for j = [1:length(x_ini)]
        if x_ini(j) <= x_max && x_ini(j) > x_second && y_ini(j) < y_middle
            counter1(i) = counter1(i) + 1;
        elseif x_ini(j) <= x_max && x_ini(j) > x_second && y_ini(j) >= y_middle
            counter2(i) = counter2(i) + 1;
        elseif x_ini(j) <= x_second && x_ini(j) > x_first && y_ini(j) < y_middle
            counter3(i) = counter3(i) + 1;
        elseif x_ini(j) <= x_second && x_ini(j) > x_first && y_ini(j) >= y_middle
            counter4(i) = counter4(i) + 1;
        elseif x_ini(j) <= x_first && y_ini(j) < y_middle
            counter5(i) = counter5(i) + 1;
        elseif x_ini(j) <= x_first && y_ini(j) > y_middle
            counter6(i) = counter6(i) + 1;
        end
    end
end
end
counter1 = counter1([1:18 21:59]);
counter2 = counter2([1:18 21:59]);
counter3 = counter3([1:18 21:59]);
counter4 = counter4([1:18 21:59]);
counter5 = counter5([1:18 21:59]);
counter6 = counter6([1:18 21:59]);
crowdedness_average = [];

for i = [1:length(counter1)]
    A = [counter1(i) counter2(i) counter3(i) counter4(i) counter5(i) counter6(i)];
    crowdedness_average_nozero(i) = mean(A(A~=0));
    crowdedness_average_zero(i) = mean(A);
end

```

```

end

figure
histogram(crowdedness_average_nozero/cell_area,8); hold on
histogram(crowdedness_average_zero/cell_area,8);
title('Grid Based Method crowdedness')
legend(' = without zeros',' = with zeros')
xlabel('Jam crowdedness (cyc/m^2)');
ylabel('Number of observations');

figure
SWspeed_final = SWspeed_final([1:18 21:59]);
for i = [length(SWspeed_final)]
    plot(crowdedness_average_zero/cell_area,SWspeed_final,'rx'); hold on
end
title('Grid Based Method crowdedness')
xlabel('Jam crowdedness [cyc/m^2]');
ylabel('Shockwave speed in [m/s]');
lsline;

figure
for i = [length(SWspeed_final)]
    plot(crowdedness_average_zero/cell_area,Q,'bx'); hold on
end
title('Grid Based Method crowdedness')
xlabel('Jam crowdedness [cyc/m^2]');
ylabel('Discharge Flow [cyc/m/s]');
lsline;

figure
for i = [length(SWspeed_final)]
    plot(crowdedness_average_nozero/cell_area,SWspeed_final,'rx'); hold on
end
title('Grid Based Method crowdedness without zeros')
xlabel('Jam crowdedness [cyc/m^2]');
ylabel('Shockwave speed in [m/s]');
lsline;

figure
for i = [length(SWspeed_final)]
    plot(crowdedness_average_nozero/cell_area,Q,'bx'); hold on
end
title('Grid Based Method crowdedness without zeros')
xlabel('Jam crowdedness [cyc/m^2]');
ylabel('Discharge Flow [cyc/m/s]');
lsline;

```

A.4 Fourth Appendix

```

counter_c1 = [];
for i = [1:18 21:fnam_length]
    load([pwd filesep 'Trajectory_data_for_analysis_IP_PT_NP_DH' filesep 'Traj_2016-06-02_' filename{i} '.mat']);
    x_ini = pos_init(:,1);
    %x_ini = x_ini(x_ini<xSL);
    y_ini = pos_init(:,2);
    index = find(x_ini<xSL);
    x_ini = x_ini(index);
    y_ini = y_ini(index);
    %radius=1;
    y_min(i) = min(y_ini);
    y_max(i) = max(y_ini);
    x_min(i) = min(x_ini);
    x_max(i) = max(x_ini);
    if i == 3 || i == 48 || i == 55
        passing_times(2) = [];
        pos_init(2,:) = [];
        %traj(2) = [];
    elseif i == 40
        passing_times(12) = [];
        pos_init(12,:) = [];
        %traj(12) = [];
    end
    counter_c1(i)=0;
    for k = [1:length(x_ini)]
        for m = [1:length(x_ini)]
            if sqrt((x_ini(k) - x_ini(m))^2 + (y_ini(k) - y_ini(m))^2) < radius
                counter_c1(i) = counter_c1(i) + 1;
            end
        end
    end
    end
    crowdedness_circles(i) = counter_c1(i) / ((pi*radius^2) * length(x_ini));
    crowdedness_circle(i) = mean(crowdedness_circles(i));
end
crowdedness_circle = crowdedness_circle([1:18 21:59]);
%crowdedness_circle_nozero = crowdedness_circle(crowdedness_circle~=0)
figure;
histogram(crowdedness_circle,8); hold on;
%histogram(crowdedness_circle_nozero,8)
title(['Range Based Method crowdedness with Radius = ' num2str(radius)])
%legend(' = without zeros', ' = with zeros')
xlabel('Jam crowdedness (cyc/m^2)');
ylabel('Number of observations');

SWSpeed_final = SWSpeed_final([1:18 21:59]);
figure;
for i = [1:length(crowdedness_circle)]
    plot(crowdedness_circle, SWSpeed_final,'rx'); hold on
end
title(['Range Based Method crowdedness with Radius = ' num2str(radius)])
xlabel('Jam crowdedness [cyc/m^2]');
ylabel('Shockwave speed [m/s]');
lslines;

figure;
for i = [1:length(crowdedness_circle)]
    plot(crowdedness_circle, Q,'bx'); hold on
end
title(['Range Based Method crowdedness with Radius = ' num2str(radius)])
xlabel('Jam crowdedness [cyc/m^2]');
ylabel('Discharge Flow [cyc/m/s]');
lslines;
end

```

A.5 Fifth Appendix

```

Z = [];
Qu = [];
Z_min = [];
for i = [1:18 21:fnam_length]
    load([pwd filesep 'Trajectory_data_for_analysis_IP_PT_NP_DH' filesep 'Traj_2016-06-02_' filename{i} '.mat']);
    x_ini = pos_init(:,1);
    %x_ini = x_ini(x_ini<xSL);
    y_ini = pos_init(:,2);
    index = find(x_ini<xSL);
    x_ini = x_ini(index);
    y_ini = y_ini(index);
    %% y_min(i) = min(y_ini);
    %% y_max(i) = max(y_ini);
    %% x_min(i) = min(x_ini);
    %% x_max(i) = max(x_ini);
    if i == 3 || i == 48 || i == 55
        passing_times(2) = [];
        pos_init(2,:) = [];
        %traj(2) = [];
    elseif i == 40
        passing_times(12) = [];
        pos_init(12,:) = [];
        %traj(12) = [];
    end
    [V,C,XY] = VoronoiLimit(x_ini,y_ini,'figure', 'off');
    %figure
    for j = [1:length(x_ini)]
        %V(C{j},:);
        Z(i,j) = polyarea(V(C{j},1),V(C{j},2));
        %plot(Z,Q(1),'rx'); hold on
    end
    %Z_min(i) = min(Z);
end
Z = Z([1:18 21:59],:);
SWSpeed_final = SWSpeed_final([1:18 21:59]);

figure
for i = [1:57]
    plot(nonzeros(Z(i,:)),Q(i)*ones(1,length(nonzeros(Z(i)))),'bx'); hold on
end

h = findobj(gca,'Type','line');
xdata=get(h,'Xdata');
ydata=get(h,'Ydata');
xdata = cell2mat(xdata);
ydata = cell2mat(ydata);

p = polyfit(xdata,ydata,1);

x1 = linspace(min(xdata),max(xdata));
y1 = polyval(p,x1);
plot(x1,y1,'b-')
title('Voronoi measure')
xlabel('Jam density [1/m^2]');
ylabel('Discharge Flow [cyc/m/s]');

figure
for i = [1:57]
    plot(nonzeros(Z(i,:)),SWSpeed_final(i)*ones(1,length(nonzeros(Z(i)))),'rx'); hold on
end

h = findobj(gca,'Type','line');
xdata=get(h,'Xdata');
ydata=get(h,'Ydata');
xdata = cell2mat(xdata);
ydata = cell2mat(ydata);

p = polyfit(xdata,ydata,1);
x1 = linspace(min(xdata),max(xdata));
y1 = polyval(p,x1);
plot(x1,y1,'r-')
title('Voronoi measure')
xlabel('Jam density [1/m^2]');
ylabel('Shockwave speed [m/s]');

```

```
figure
histogram(xdata,25)
title('Voronoi measure')
xlabel('Jam density [1/m^2]');
ylabel('Number of observations');
```

A.6 Sixth Appendix

```

counter_EWD = [];
for i = [1:18 21:fnam_length]
    load([pwd filesep 'Trajectory_data_for_analysis_IP_PT_NP_DH' filesep 'Traj_2016-06-02_' filename{i} '.mat']);
    x_ini = pos_init(:,1);
    %x_ini = x_ini(x_ini<xSL);
    y_ini = pos_init(:,2);
    index = find(x_ini<xSL);
    x_ini = x_ini(index);
    y_ini = y_ini(index);
    radius=1;
    y_min(i) = min(y_ini);
    y_max(i) = max(y_ini);
    x_min(i) = min(x_ini);
    x_max(i) = max(x_ini);
    if i == 3 || i == 48 || i == 55
        passing_times(2) = [];
        pos_init(2,:) = [];
        %traj(2) = [];
    elseif i == 40
        passing_times(12) = [];
        pos_init(12,:) = [];
        %traj(12) = [];
    end
    counter_EWD(i) = 0;
    for j = [1:length(x_ini)]
        for k = [1:length(x_ini)]
            counter_EWD(i) = counter_EWD(i) + exp(-(radius^2)*((x_ini(k)-x_ini(j))^2 + (y_ini(k)-y_ini(j))^2));
        end
    end
    counter_EWD(i) = counter_EWD(i) / (length(x_ini));
end
SWSpeed_final = SWSpeed_final([1:18 21:59]);
counter_EWD = counter_EWD([1:18 21:59]);
counter_EWD = counter_EWD / (pi*radius^2);

figure
plot(counter_EWD,SWSpeed_final,'rx'); hold on
title('Exponentially weighted distance measure')
xlabel('Jam crowdedness [cyc/m^2]');
ylabel('Shockwave speed [m/s]');
lslines;

figure
plot(counter_EWD,Q,'bx'); hold on
title('Exponentially weighted distance measure')
xlabel('Jam crowdedness [cyc/m^2]');
ylabel('Discharge Flow [cyc/m/s]');
lslines;

figure
histogram(counter_EWD,8);
title('Exponentially weighted distance measure')
xlabel('Jam crowdedness [cyc/m^2]');
ylabel('Number of observations');

```


A.7 Seventh Appendix

```
for i = [1:18 21:fnam_length]
    load([pwd filesep 'Trajectory_data_for_analysis_IP_PT_NP_DH' filesep 'Traj_2016-06-02_' filename{i} '.mat']);
    x_ini = pos_init(:,1);
    %x_ini = x_ini(x_ini<xSL);
    y_ini = pos_init(:,2);
    index = find(x_ini<xSL);
    x_ini = x_ini(index);
    y_ini = y_ini(index);
    y_min(i) = min(y_ini);
    y_max(i) = max(y_ini);
    x_min(i) = min(x_ini);
    x_max(i) = max(x_ini);
    if i == 3 || i == 48 || i == 55
        passing_times(2) = [];
        pos_init(2,:) = [];
        %traj(2) = [];
    elseif i == 40
        passing_times(12) = [];
        pos_init(12,:) = [];
        %traj(12) = [];
    end
    counter_HWMD(i) = 0;
    for j = [1:length(x_ini)]
        for k = [1:length(x_ini)]
            if k ~= j
                counter_HWMD(i) = counter_HWMD(i) + (1 / sqrt(((x_ini(k) - x_ini(j))^2 + (y_ini(k) - y_ini(j))^2)));
            end
        end
    end
    counter_HWMD(i) = counter_HWMD(i) / (length(x_ini));
end
SWSpeed_final = SWSpeed_final([1:18 21:59]);
counter_HWMD = counter_HWMD([1:18 21:59]);

figure
plot(counter_HWMD,SWSpeed_final,'rx'); hold on
title('Harmonically Weighted Mean measure')
xlabel('Jam crowdedness [m]');
ylabel('Shockwave speed [m/s]');
lsline;

figure
plot(counter_HWMD,Q,'bx'); hold on
title('Harmonically Weighted Mean measure')
xlabel('Jam crowdedness [m]');
ylabel('Discharge Flow [cyc/m/s]');
lsline;

figure
histogram(counter_HWMD,8);
title('Harmonically Weighted Mean measure')
xlabel('Jam crowdedness [m]');
ylabel('Number of observations');
```

A.8 Eighth Appendix

```
for i = [1:18 21:fnam_length]
    load([pwd filesep 'Trajectory_data_for_analysis_IP_PT_NP_DH' filesep 'Traj_2016-06-02_' filename{i} '.mat']);
    x_ini = pos_init(:,1);
    %x_ini = x_ini(x_ini<xSL);
    y_ini = pos_init(:,2);
    index = find(x_ini<xSL);
    x_ini = x_ini(index);
    y_ini = y_ini(index);
    y_min(i) = min(y_ini);
    y_max(i) = max(y_ini);
    x_min(i) = min(x_ini);
    x_max(i) = max(x_ini);
    if i == 3 || i == 48 || i == 55
        passing_times(2) = [];
        pos_init(2,:) = [];
        %traj(2) = [];
    elseif i == 40
        passing_times(12) = [];
        pos_init(12,:) = [];
        %traj(12) = [];
    end
    minimumdistance(i) = 10;
    for j = [1:length(x_ini)]
        for k = [1:length(x_ini)]
            if k ~= j
                if sqrt((x_ini(k)-x_ini(j))^2 + (y_ini(k)-y_ini(j))^2) < minimumdistance(i)
                    minimumdistance(i) = sqrt((x_ini(k)-x_ini(j))^2 + (y_ini(k)-y_ini(j))^2);
                end
            end
        end
    end
end

SWSpeed_final = SWSpeed_final([1:18 21:59]);
minimumdistance = minimumdistance([1:18 21:59]);

figure
plot(minimumdistance,SWSpeed_final,'rx'); hold on
title('Minimum Distance Measure')
xlabel('Jam crowdedness [m]');
ylabel('Shockwave speed [m/s]');
lsline;

figure
plot(minimumdistance,Q,'bx'); hold on
title('Minimum Distance Measure')
xlabel('Jam crowdedness [m]');
ylabel('Discharge Flow [cyc/m/s]');
lsline;

figure
histogram(minimumdistance,8);
title('Minimum Distance Measure')
xlabel('Jam crowdedness [m]');
ylabel('Number of observations');
end
```

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