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Cyclist's waiting time estimation at intersections, a case study with GPS traces from Bologna

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Abstract

Waiting time plays an important role in the cyclists' route choice, most likely because cyclists, after a stop, need to pedal harder to regain their previous speed. Literature review highlights that cyclists generally overestimate waiting time approximately three to five times higher than their actual waiting time. The aim of this paper is to quantify cyclists' waiting time in function of specific intersection characteristics and person attributes. This aim is achieved in two steps: (1) a recent algorithm that estimates cyclists' waiting time from GPS traces is validated, using data from a manual survey, (2) a second manual survey has been conducted to test the representativeness of a big data set of 270,000 GPS traces recorded in the city of Bologna, Italy; the same survey also showed how many cyclists pass with the red signal for different maneuvers; and finally (3) the mentioned algorithm is applied to the big data set in order to estimate the waiting time for different intersection types and cyclist attributes. Such estimations have not been addressed in literature due to the difficulty of associating the cyclists' waiting times with infrastructure elements based using GPS traces. Results show that waiting time represents a not-negligible share of the bike trip (11% of total trip duration). On average, particularly large waiting times have been found (1) at complex intersections by (2) for cyclists younger than 25 years old, (3) for infrequent cyclists and (4) for women. During rush hour, cyclists have recorded waiting times only 6% above the daily average, demonstrating that traffic congestion has a limited effect on waiting times. Furthermore, approximately 14% of all cyclists have crossed the red traffic light, especially when the opposite traffic volume is not high and there is good visibility. The study contributes to provide a novel and validated tool to evaluate waiting times of cyclists from GPS traces, which can support the calibration of cyclists route choice models.

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Keywords: waiting time; big data; cyclist; GPS trace; manual survey; map matching

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1. Introduction

The impact of stops and delays during bicycle trips has been analyzed in several studies. Börjesson and Eliasson (2012) have found that the perception of a one-minute stop at a traffic signal equals 3.1 min of cycling. More recently, Fioreze et al. (2019) have shown that most cyclists considerably overestimate their waiting time: cyclists' perceived waiting time was approximately five times higher than their actual waiting time. These studies underpin the importance of analyzing the cyclists' waiting time. Indeed, reducing waiting times for cyclists, for example by reducing the total traffic light cycle time or by extending the green phase for cyclists, is a cost-efficient strategy to increase the bicycle level of service, whereas other aspects (safety, separated bicycle infrastructure, road quality, segregating bike flows from car flows, etc.) require much more expensive infrastructural changes (see Gillis et al. (2020)). In general, average bicycle delays and waiting times could be derived from the characteristics of the traffic light scheme (traffic light phases and cycle) by calculating the statistically expected average waiting time (see Gillis et al. (2020)). Nowadays, GPS devices allow to easily record large samples of trip traces, thus supporting the evaluation of the cyclists' waiting times (see Rupi et al. (2020)), as well as evaluate traffic volumes (see Pogodzinska et al. (2020), Rupi et al. (2019)); in any case, big data does not means they represents well th cyclist population (see huber et al. (2020), Lißner and Huber (2021))) The raw GPS traces consist of geo-located points associated with timestamps; these points are usually recorded with an average frequency of a few seconds on standard smartphones and the device stops recording points while it is not moving. Estimating trip-related attributes from GPS traces, like speed profiles or waiting times, raises multiple challenges. The first challenge concerns the quality of the single GPS trace, whose position errors should be verified and corrected, if possible; otherwise, the respective trace should be eliminated from the data sample. The second challenge involves the map matching process, as the effective route chosen by the user needs to be guessed, using the scattered and sometime imprecise GPS points. Reliable map matching is difficult even for more sophisticated algorithms. The last main challenge is to find a method to extrapolate the speed profiles and waiting times from the map-matched GPS traces and eventually to attribute them to single infrastructure elements. For these reasons, only few studies have attempted to estimate the cyclist's speed from GPS traces (see Strauss et al. (2017), Clarry et al. (2019) and Laranjeiro et al. (2019)), and only a previous study has dealt with the cyclists' waiting time estimation (see Rupi et al. (2020)). Furthermore, some works focused on estimating traffic delays (see Gillis et al. (2020), Strauss et al. (2017), Kircher et al. (2018)) which can be more easily evaluated, but are less significant, mainly because a cyclist suffers waiting times, which imply to stop and a significant effort to re-accelerate; delays mean typically a slowdown of the cyclists, which is less tiring than a complete stop. The aim and novelty of the paper is to apply an algorithm described on a previous study (see Rupi et al. (2020)), which allows to estimate the cyclists' waiting times from GPS traces, to a big data set of 270,000 GPS traces, and successively investigate cyclists and infrastructure attributes which can condition these times, which are not yet quantified in literature. The paper is structured as follows: section 2 presents the used methodology for the case study, section 3 and 4 show respectively the validation of the used algorithm and the representativeness test of the big data sample. Results and their discussion are presented in section 5, and the conclusions are showed on section 6.

2. Method

The analysis consists of three different phases: 1) Validating the algorithm that estimates waiting times from GPS traces by means of a manual survey; 2) Applying the algorithm to the GPS data sample in order to test its representativeness using a second manual survey; 3) Analysing the results obtained from applying the algorithm to the GPS database. The algorithm that estimates waiting times from GPS traces is part of the SUMOPy simulation suite (see SUMOPy (2021)), which provides also all the other functionalities such as network conversion, mapmatching and different analysis methods. The road network is imported from the OpenStreetMap database (see OSM (2021)) and converted to a SUMO transport network, while retaining most important edge attributes such as shape, speed limits, access rights and lane configurations; the network has been manually corrected, with a particular focus on the bicycle paths, since OSM network can contain some errors and in a way to model all the possible links usable by bikes.

The GPS traces have been recorded by cyclists using a smartphone app. During a pre-processing phase, GPS traces are matched to the transportation network and unsuitable traces are eliminated in a filtering process: GPS traces out of the study area or with too high speeds (for bicycles) are discarded. Frequently, GPS points cannot be joined by roads of the network because of connection problems. Typically, many traces cannot be mapmatched and must be eliminated; this occurs if no route can be found that follows the GPS points. The remaining traces are then projected, point-by-point, to a presumed location along the previously matched route. In this way, the position over time and the speed profile of the respective cyclist can be reconstructed. This method further allows to estimate waiting times and locate them on the network: the waiting time is the time when the travel speed between successive points falls below the threshold of $1m/s$ while the respective points are used to identify the corresponding edges, nodes or even maneuvers within intersections. This last phase represents the innovative part of the algorithm and allows to directly evaluate the cyclists' waiting time – that is the time when the cyclist actually stops. This means the delays caused by slow downs are not measured as they are less significant from a transportation point of view. However, this sophisticated analysis requires good GPS traces without significant recording noise, which would make some results ambiguous. For this reason, a further and effective filtering process is associated with this last phase. In order to identify potential factors impacting the cyclists' waiting time, the cyclists of the database are grouped by: 1) personal attributes (age and gender), 2) time interval (rush hour) and 3) specific infrastructure elements (edges, nodes and link-to-link maneuvers). In addition, traffic counts of the second survey have also allowed to quantify the cyclists passing with the red light and to identify the conditions which encourage this dangerous maneuver.

3. Algorithm validation

The validation of the algorithm estimating the cyclist's waiting times from recorded GPS traces has been conducted with data from the first manual survey. This survey has required a certain number of test cyclists who recorded their GPS traces with the Endomondo smartphone app while manually measuring their real waiting times. Two hundred traces have been recorded by three test cyclists in 19 different maneuvers while manually measuring their waiting time using a chronograph (see Tab.1): 5 right turns, 4 left turns and 10 crossings have been analyzed in four highly frequented intersections with traffic lights in Bologna, Italy (see Rupi et al. (2019), Schweizer et al. (2020)). Three different smartphones have been used for recording the GPS traces, characterized by different sampling rate. In general, a GPS trace is recorded every 5 in-motion seconds on average and the device stops registering when the bike no longer moves. In particular, the three devices had sampling rates of 2, 7 and 9 in-motion seconds per point to test the algorithm's sensibility. The low sample rate and frequent inaccurate position of the GPS points - generally in the order of 10 meters - present the main problems for estimating accurately the waiting time of cyclists at different infrastructure elements. The recorded traces have been imported in SUMOPy and the simulated waiting times have been evaluated and compared with the measured waiting times. Table 1, describes the considered maneuvers, the GPS traces recorded on each maneuver, the effective number of used GPS traces – after applying the filtering process – and finally a comparison between measured and simulated values: waiting times and number of traces which recorded a waiting time. It is worth noting that most of the excluded GPS traces have a low recording sampling rate of GPS points, which renders the map-matching of the GPS trace to the road network, as well as the identification of waiting times, very difficult. The correlation between measured and simulated values has been quantified with a linear regression of waiting time values for each maneuver: even considering each maneuver separately, the linear regression between measured and monitored waiting times shows a good correlation – even with low sample rates - and also the average values of waiting times for each maneuver are remarkably similar. The linear regression between all the measured and simulated waiting times (see figure 1a) shows a high R^2 (0.95). Moreover, the coefficient of the interpolation line and the constant term are close to 1 and 0, respectively, indicating a good estimation of waiting times. The regression shows a relatively small standard error of 7.3 seconds, and the 95% confidence intervals of the slope and the constant term are respectively 1.062 to 1.153 and -1.356 to 1.942, with a P-Value associated to the slope smaller than 0.0001. Figure 1a shows that some of the small measured waiting times have not been intercepted by the algorithm; this is mainly due to the low sample rate of the GPS points of the recorded traces. In fact, observing table 1, it is possible to see that when evaluating the waiting times of maneuvers with a low sampling rate - 1 point every 9 seconds - many traces show no waiting times differently from the measured values - mainly due to the connection number 11, where averaged measured waiting time is approximately 12 seconds. To test the model validity, the regression has been done for the three dataset separately, showing similar R^2 (0.99, 0.87 and 0.94), similar trend line equations ($y = 1.09x - 0.03$, $y = 1.26x - 3.67$ and $y = 1.07x + 0.32$), and similar standard errors (4.1, 9.4 and 6.7). The GPS data sample with the lowest sample frequency of GPS points shows the worse result, but still acceptable.

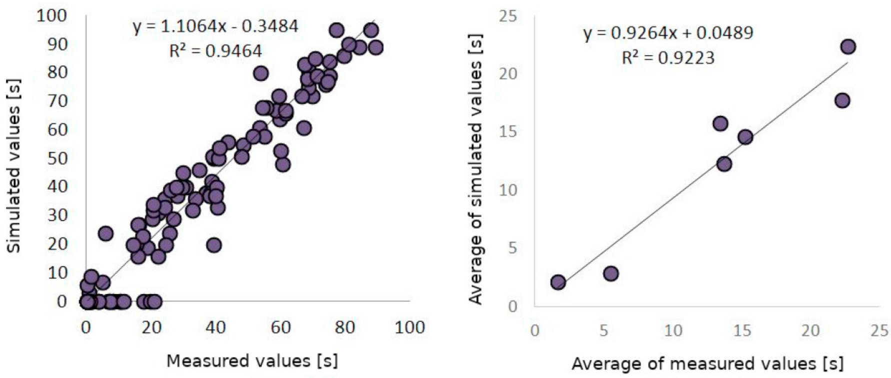

Fig. 1: Comparison between measured and simulated waiting times for testing algorithm validity through first manual survey (a), and to test sample representativeness through the second survey (b).

Table 1: Description of the monitored maneuvers during the first survey and simulated waiting times (WT)

Maneuver	N trips	Av. N. GPS points	Av. sample rate	N trips - after filters	Av. measured WT	Av. simulated WT	Meas. trips no WT	Simul. trips no WT	Coefficient trendline	Constant trendline	Rsquare trendline
	/	/	[s/points]	/	[s]	[s]	[%]	[%]	/	/	/
1*	11	39	3,63	10	35,4	28,7	27	50	1,05	0,85	0,99
2*	11	20	3,89	10	38,2	45,6	36	30	1,09	-0,22	0,99
3*	11	51	3,62	2	/	/	/	/	/	/	/
4*	11	43	4,04	9	76,6	83,2	0	0	1,04	3,6	0,81
5	10	7	13,65	3	/	/	/	/	/	/	/
6	10	5	24,45	1	/	/	/	/	/	/	/
7	10	6	15,42	0	/	/	/	/	/	/	/
8	10	9	11,16	10	41,3	48,6	0	20	1,12	2,26	0,91
9	10	8	9,86	10	18,7	25,3	10	30	1,57	-4,04	0,94
10	10	7	13,5	6	26,2	31,83	0	17	1,47	-6,77	0,97
11	10	6	10,4	9	12,2	3	0	89	0,43	-2,25	0,06
12	12	13	7,04	5	0	0	100	100	0	0	1
13	13	15	7,03	12	12,3	13,17	67	58	1,01	0,72	0,99
14	11	16	7,9	2	/	/	/	/	/	/	/
15	10	16	6,94	7	20,7	21,71	43	43	0,95	2,02	0,93
16	10	15	8,53	6	21,5	24,71	44	44	1,1	0,52	0,99
17	10	16	8,28	10	28,7	33,9	0	10	1,05	3,91	0,79
18	10	15	7,63	10	28,5	29,8	20	40	1,15	-3,03	0,98
19	10	14	8,1	7	37,9	39,57	14	14	1,08	-1,32	0,94

*Exclusive cycleway

4. Sample representativeness

Approximately 270,000 GPS traces of bicycle trips were recorded from April to September 2017, thanks to the 'Bella Mossa' campaign (see Città Metropolitana di Bologna (2017)). All the collected data complies with EU

(European Union) General Data Protection Regulation; the data is securely stored, and all analyses are done on aggregated datasets where the data cannot be traced back to individual users. This method ensures that participants remain completely anonymous. This database also provides information about cyclists' age and gender. As the pre-processing is composed by many filters, and only real and high-quality GPS traces are required to estimate waiting times, the final sample is composed of 105,000 GPS traces, and approximately 12,400 have been recorded during the morning rush hour – from 7am to 10am - on weekdays, with a sample rate of about 7 trace per cyclist. As described in section 1, big data does not mean representative data: to test the representativeness of the used data sample, the average waiting times monitored with a second manual survey performed between April and May 2019 during the morning rush hours on weekdays - from 7am to 10am - have been compared with the simulated waiting times from the Bella Mossa sample of GPS traces recorded during same time interval and by considering the whole database from April to September 2017. Should the compared values were similar then this would mean: 1) The used database is representative of the cyclist population in the city of Bologna and 2) The validity of the algorithm is again confirmed. The second survey has focused on measuring the waiting times of casually passing cyclists while performing the same maneuvers as the first survey. In addition, the four opposite maneuvers of the first four crossing maneuvers have been monitored. Table 2 shows the comparison between measured and simulated waiting times: these times become similar only for maneuvers with at least 100 counted trips, because cyclists' waiting times have a large deviation; in fact, the average absolute error between the average of measured and simulated waiting times is just 1.73 seconds for these maneuvers, while is 8.73 for the others. By considering only the maneuvers with at least 100 counted trips, figure 1b shows a good correlation between the simulated values from the big data sample and the measured values, thus confirming the database's representativeness, despite the temporal delay of two years between the measured and simulated values. The regression shows a standard error of 2.3 seconds, while the 95% confidence intervals of the slope and the constant term are 0.6171 to 1.236 and −7.458 to 3.945, respectively; the P-Value associated with the slope equals 0.0006.

5. Results and Discussion

Applying the algorithm to the GPS data sample, the average cyclists' waiting time, averaged over all intersections (signalized and not signalized), has resulted in 1.9 second, while the average waiting times at signalized intersections has amounted to 4.4 seconds (see figure 2). Figure 2 refers to those 4,390 nodes which were visited by at least 100 cyclists and representing 50% of all network nodes. The labels of figure 2 have the following meaning: 'All' means all 4,390 nodes and 'Rush' means only GPS traces recorded during the morning rush hour from 7am to 10am of work-days, 'TL' means signalized intersections and 'N conn' means the number of lane to lane connections (or maneuvers) allowed in the intersection, which gives also an idea of the intersection complexity. The minimum number of 100 cyclists per intersection is imposed to filter only representative values, as explained in section 4. The bars indicate the first, second and third quartiles, as well as the minimum and maximum values, considering a maximum Whisker length equal to 1.5 times the interquartile range. This figure shows that the average waiting time does not much increase with the intersection complexity of intersection without traffic lights. At signalized intersections, average waiting times vary from approximately 3 seconds to almost 6 seconds for intersections which allow less than 5 and from 5 to 15 maneuvers, respectively; this variation is mainly due to the longer red duration at the traffic light for cyclists at larger intersections. However, these short waiting times can be partially explained by the fact that many users cross the intersection with red light, especially in small intersections, as described below. Average waiting times for different maneuvers within the intersection are shown in figure 3, based on a total of 6,822 lane-to-lane connections; this corresponds to only 15% of all network because only connection used by more than 100 cyclists have been considered; in this figure 'L conn' stands for connection length. The cyclists' waiting time is on average 11% of the total trip duration and the rush hour congestion increases the cyclists' average trip waiting time of only 6% approximately. This fact confirms that cyclists are not much affected by traffic congestion. The connection length has only minimal affect on cyclist's waiting times, whereas the connection typology does have a noticeable impact on waiting time – turns, especially left turns, generate larger waiting times. It is worth noting that female cyclists accumulate on average 17% more waiting time than men and that cyclists below 25 years of age accumulate on average 10 % more of trip waiting time with respect to the population average; infrequent cyclists, who recorded less than 50 GPS traces during the study period, record on average 22% more waiting time respect to frequent cyclists, who recorded more than 150

Table 2: Measured (1S: first survey; 2S: second survey) and simulated (S) waiting times (WT)

Maneuver	Maneuver type	Visibility	Opposite traffic	N trips (2S)	N WT (2S)	% Ignore red at TL (2S)	% WTs (2S)	Average WT (1S)	Average WT (2S)	N trips (S)	N WT (S)	% waiting times (S)	Average WT (S)
1	crossing	high	high	257	139	3.9	54.09	35.4	22.67	159	72	45.28	22.38
2	crossing	high	high	28	11	7.1	39.29	38.2	5.15	7	0	0.00	0.00
3	crossing	high	high	96	68	7.3	70.83	0.0	33.01	44	24	54.55	32.14
4	crossing	high	high	91	59	0.0	64.84	76.6	32.76	106	54	50.94	16.93
5	rigth turn	low	medium	20	3	55	15.00	0.0	4.02	4	2	50.00	5.75
6	crossing	low	medium	277	146	18.4	52.71	0.0	22.23	281	126	44.84	17.77
7	left turn	low	medium	22	9	40.9	40.91	0.0	19.16	24	5	20.83	6.96
8	crossing	low	medium	101	35	11.9	34.65	41.3	13.43	116	43	37.07	15.78
9	rigth turn	medium	low	100	12	18.0	12.00	18.7	1.82	158	46	29.11	8.57
10	left turn	low	medium	146	68	19.2	46.58	26.2	15.23	169	79	46.75	14.63
11	rigth turn	medium	medium	166	16	25.9	9.64	12.2	1.70	181	18	9.94	2.10
12	crossing	low	low	49	5	38.8	10.20	0.0	1.64	94	16	17.02	4.48
13	crossing	low	low	156	39	37.2	25.00	12.3	5.50	459	54	11.76	2.89
14	rigth turn	low	low	3	0	0.0	0.00	0.0	0.00	19	5	26.32	11.32
15	crossing	low	medium	57	37	0.0	64.91	20.7	23.58	35	9	25.71	8.37
16	left turn	low	medium	2	1	0.0	50.00	21.5	30.90	14	5	35.71	11.57
17	left turn	low	medium	8	2	0.0	25.00	28.7	11.58	13	3	23.08	5.54
18	crossing	low	medium	77	17	0.0	22.08	28.5	7.34	93	34	36.56	13.45
19	rigth turn	low	low	9	1	0.0	11.11	37.9	1.91	9	2	22.22	2.33
20	crossing	high	high	100	58	1.0	58.00	/	22.66	106	27	25.47	14.11
21	crossing	high	high	25	16	8.0	64.00	/	28.21	9	6	66.67	10.89
22	crossing	high	high	15	4	20.0	26.67	/	10.34	11	6	54.55	20.36
23	crossing	high	high	112	39	0.0	34.82	/	13.70	90	30	33.33	12.33

GPS traces during the study period. Waiting times are widely distributed at single intersections (with or without traffic light), because they may depend on many factors: opposite flow, share of green phase, the intention to pass with red light, visibility, caution and so on, as shown on figures 2, 3. Estimating waiting time at traffic lights is particularly challenging because it depends significantly at which traffic light phase the cyclist arrive – a quantity not measurable with the present data set. Table 2 shows how the different maneuver types relate to the waiting times from the first and second survey, where the simulated waiting times have been obtained by applying the algorithm to the GPS data sample. The Table shows that 14.3% of the monitored cyclists during the second survey have passed with red at the traffic lights; in fact, the waiting times measured during the first survey, where test drivers always respected the traffic lights, are in most cases higher than the actual waiting times observed during the second survey. From the same table it appears that cyclists are more cautious during maneuvers where visibility is low or where traffic flow is high. In conditions of medium-low traffic and good visibility cyclists tend to cross more frequently the road with the red signal.

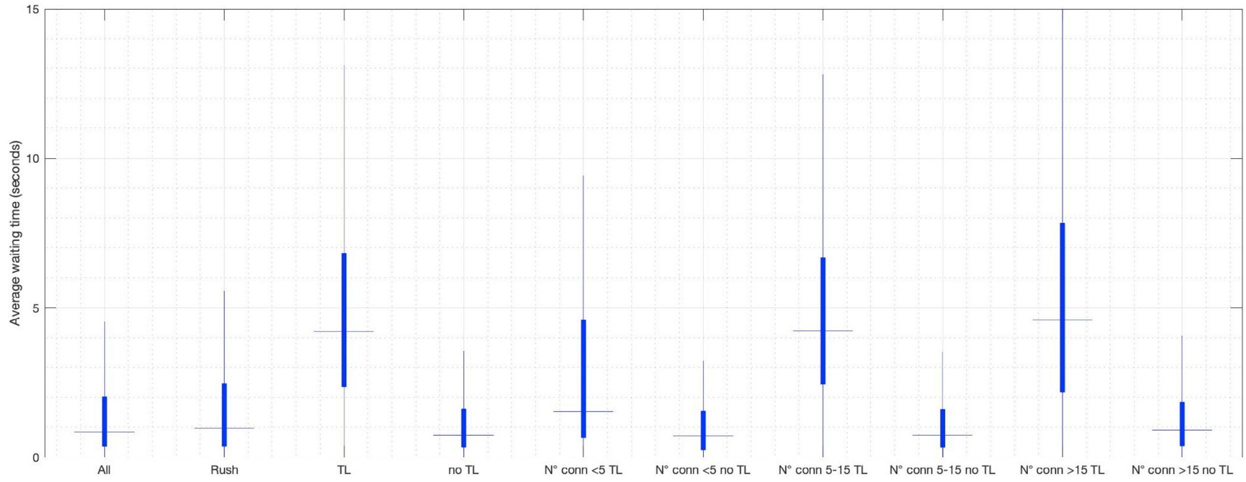

Fig. 2: Box plots of trip waiting times on different node types

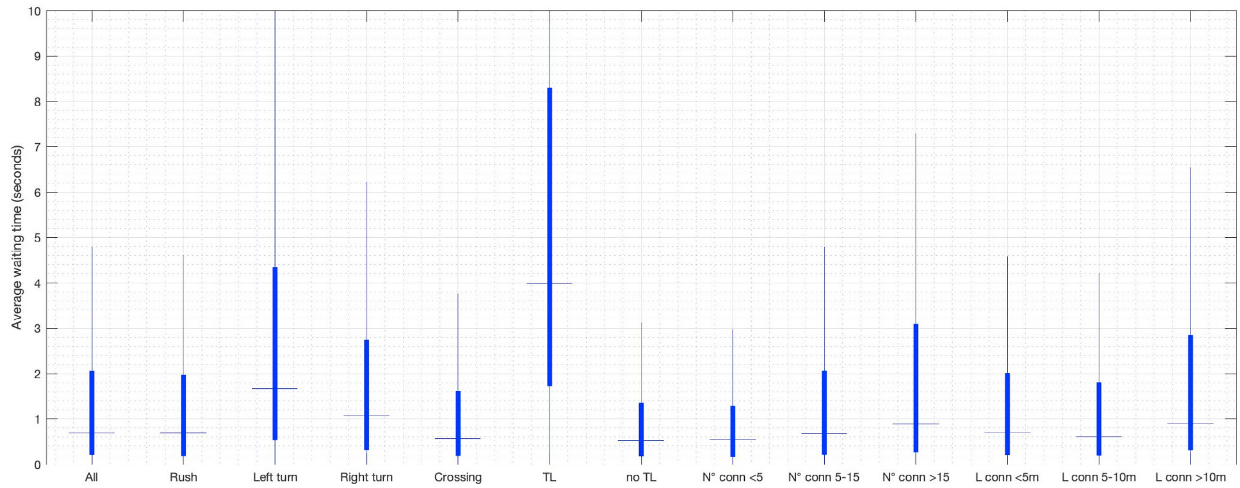

Fig. 3: Box plots of trip waiting times on different lane-to-lane connection types

6. Conclusion

A recently proposed algorithm, that estimates the cyclists' waiting times from GPS traces and matches these to specific infrastructure elements, has been validated and applied to a large sample of GPS traces, after successfully testing the big data sample's representativeness. Waiting time is found to be a significant share of the cyclists' travel time (11% on average for this case study). The cyclists' waiting time is proven to be susceptible to infrastructure specifics such as intersection complexity (number of allowed maneuvers), the presence of the traffic light, type of maneuver and visibility. Also, opposite traffic plays an important role on cyclists' waiting time on both uncontrolled and signalized intersections, especially when cyclists want to cross with the red signal. Another important finding is that the waiting time during rush hour is only approximately 6% higher than the daily average, which highlights that the cyclists' waiting times are little affected by traffic congestion. The type of cyclist also affects the cyclists' waiting time: female cyclists record on average 17% higher waiting times with respect to men, people of age below 25 years record average waiting times 10% above the average of all cyclists and infrequent cyclists record on average a 22% higher waiting time with respect to frequent cyclists. This behavior is amplified by the fact that on average 14.3% of all cyclists cross with red light, especially when there is a decent visibility and and a limited traffic volume in the opposite direction. The present article provides a series of important attributes that should be taken into account when calibrating a model that estimates waiting time distributions of cyclists for specific maneuvers at intersections. Such models could be useful for the routing of cyclists in micro simulations or for route choice models. Furthermore the results help to design an efficient cyclist network, which allows to reduce waiting time and to increase the cyclists' safety, mainly avoiding irregular behavior of cyclists at traffic light. However, future studies should test the algorithm with different GPS data recorded in different urban settings in order to test the transferability the results.

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