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Traffic surveys and GPS traces to explore patterns in cyclist's in-motion speeds

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Abstract

Speed and travel time of cyclists play important roles in the cyclist's route choice and therefore there is a growing need on estimating the dynamic attributes of cyclists. Being able to quantify bicycle speeds on various facilities can help provide suitable accessibility measures based on estimates of travel time by bicycle and to calibrate and validate microsimulation models of cyclist's behavior. Route choice and speed profiles may vary significantly among cyclists, depending on infrastructure characteristics as well as their personal characteristics (e.g., physical fitness and risk perception). The aim of this paper is to quantify how the personal and network attributes influence the cyclist's speed, combining a big data sample of 270,000 GPS traces recorded in the city of Bologna, Italy, with a manual traffic survey. The novelty of the study regards the application to the data set of an algorithm that estimates travel times from map matched GPS traces and associates them with infrastructure attributes, after a successful validation of the data sample with manual observations and after testing its representativeness. The algorithm first estimates cyclist's trip waiting times and those recorded on specific infrastructure elements from the GPS traces – which represents an innovation in the literature - and then obtains travel time as a difference with the trip duration. Results are sometimes different from those obtained in other studies, show a high correlation between the cyclist's dynamic attributes and both cyclist's typology and infrastructure attributes. The most interesting results are that average travel speed increases with road width, the number of lanes, road length and road priority. In the case study, average speeds on larger roads shared with motorized vehicles are even greater than those on separate level bikeways, which contradict previous studies. Male cyclists record on average an 11% higher speed than women, and faster cyclists have an age between 25 and 35 years old. Frequent cyclists are on average 5% faster than infrequent cyclists and cyclists even increase the average speed during rush hour of approximately 2%, without being affected by traffic congestion.

Keywords: travel time; speed, cyclist; GPS trace; manual survey; map matching

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1. Introduction

In recent years, there has been a growing interest towards bicycles followed by an increasing number of studies on cyclist's behavior. Especially, the bicycle as a mode of transportation can reduce pressure on urban roads as stated by Parkin and Wardman (2007), use of fuel and consequently air pollution, according to Federal Highway Administration (1993), Kendrick et al. (2011) and Koorey and Mangundu (2010). Moreover, cyclist infrastructure's cost is considerably lower than other modes of transport, according to Gotschi (2011). For these reasons, local and regional transport authorities encourage people to use bicycle as one of the main modes of transportation, as stated by Kassim et al. (2020). Cycling is characterized by high travel-time reliability: this aspect is a strong point to promote cycling mobility, as the uncertainty of travel time is a vital factor for accessibility (see Liao and van Weeet al. (2017)). Being able to quantify and predict bicycle speeds on various facilities can help provide idoneous accessibility measures based on estimates of bike travel times (see Krizek et al. (2010)); however, transportation policy or technology should not only advance the overall accessibility score but also improve the least advantaged group's accessibility levels, thus narrowing their difference to the average (see Pereira et al. (2017)). Speeds can be obtained from field data collected along various bicycling facilities; while the procedure for estimating travel speeds for travel by transit and auto is well established, the literature is rather scarce for cycling (see Willberg et al. (2021)). According to Allen et al. (1998), the majority of the reported speeds in the literature has been between 12 km/h and 20 km/h. Other studies used mean speeds between 15 km/h and 18 km/h (Botma (1995); Thompson et al. (1997)). Khan et al. (2001), using video image data collection and analysis techniques found a mean of 24.8 km/h on an exclusive bicycle route in Denver, CO. Despite the increasing need, the lack of cycling data and access to it is still a common challenge (see Willberg et al. (2021); Krizek et al. (2010)). However, today GPS traces are becoming important as data source for the urban transport planning. Starting from them, it is possible to build the spatial distribution of cyclist's trips in the city during different days, to determine flows and much other important information as the number of stops per trip or the distribution of stop times and speed models, as said by Laranjeiro et al. (2019). Furthermore, with GPS data it is possible to construct more effective route choice models, as stated by Zimmermann et al. (2017) and Schweizer et al. (2020) because they acquire information concerning real choices of cyclists, allowing a more accu- rate infrastructure improvement analysis. In this regard, travel time is surely an important factor affecting the route choice of cyclists. The cyclist's total travel time consists of the waiting time and the in-motion time. Cyclist's waiting times on urban networks represent on average a significant amount of the total duration of the whole trip and they are different because of cyclist and maneuver types, as described in Rupi et al. (2020). Moreover, the cyclist speed, which is difficult to measure accurately with traditional count methods, is also one of the most important factors for incident analysis (for example see Thompson et al. (1997)), because speed just before the crash is directly related to injury seriousness. With the popularity increase of the bicycle, new safety concerns are introduced, as discussed by Dozza et al. (2018), searching for roads with more reliability and safety for cyclists. In relation to the great importance of total travel time in the route choice behavior of cyclists, the chosen route is often significantly different from the shortest one in case the alternative route offers a high share of reserved bikeways, a high share of low priority roads, a low intersection density or a low share of roads with mixed traffic (cyclists with buses and pedestrians), as explained by Rupi et al. (2019). Speeds and delays at intersections are important for purposes like transport planning, navigation and route studies, including their daily variations. In a study by Iacono et al. (2007), GPS data of relatively few participants is used to predict travel speeds on street-level, separate level, and mixed traffic facilities, finding that cyclists tend to travel along various types of facilities at different speeds. In particular, according to their study, travel speeds on separate level facilities were slightly higher than those for street-level and mixed traffic facilities. Moreover, they discovered that cyclists making longer trips tend to be faster than others, and gender and age have a positive and statistically significant effect on bicycle speed. Strauss and Miranda-Moreno (2017) observed that highest momentary speeds are reached, on average, on arterial roads instead of local ways. Moreover, they found that speeds are greater along road segments with bicycle infrastructure than those without. Furthermore, they noticed that highest speeds are reached by cyclists who travel for work or school purposes, during morning peak hour on intersections without red light systems at both road extremities. As described by Clarry et al. (2019), the negative effect of cycling uphill on speed is stronger than the positive effect of travelling downhill. Furthermore, bicycle infrastructures such as bike routes and segregated bike lanes significantly increase cycling speed, as do larger roads. All this information might be used to direct cycling policy of a city. For Yu et al. (2020) is essential to obtain accurate valuations of urban traffic models for the development of transport systems and the efficient functioning of smart mobility platforms. The aim of the paper is to apply an in-motion velocity estimation algorithm based on GPS traces (see Rupi et al. (2020)) to a big data set of 270,000 GPS traces. Manual traffic surveys have allowed to validate this algorithm and to confirm its representativeness. From the obtained in-motion times it has been possible to identify the relationship with specific infrastructure attributes and personal attributes. Therefore, this paper provides a contribute for addressing what the authors believe is one of the gaps in existing knowledge regarding bicycle facilities and travel. The paper is structured as follows: section 2 presents the used methodology for the case study and the data, section 3 shows the validation of the used methodology to evaluate the in-motion speed of cyclists and the representativeness test of the big data sample. Results of the analysis of cyclist's in motion speeds are presented in section 4 and their discussion, as well as the conclusions are showed on section 5.

Table 1. Measured and simulated values of the average in-motion speed on the monitored sections.

Section	Measured v (m/s)	Simulated v (m/s)	$\|\|\Delta v\|\|$ (m/s)	Δv (%)
Tang. delle Biciclette, Via Santo Stefano	5.01	5.44	0.43	9%
Tang. delle Biciclette, Via Saragozza – North direction	4.22	4.60	0.38	9%
Tang. delle Biciclette, Via Saragozza – South direction	5.88	6.55	0.67	11%
Via Sabotino – East dir.	4.74	5.26	0.52	11%
Via Sabotino – West dir.	4.61	4.75	0.14	3%
Via Irnerio	5.35	5.01	0.34	6%
Via Farini	4.10	3.86	0.24	6%
Via Ugo Bassi - West dir.	4.63	4.69	0.06	1%
Via Ugo Bassi - East dir.	4.60	4.28	0.32	7%
Via Riva di Reno – East dir.	3.95	4.23	0.28	7%
Via Riva di Reno – West dir.	5.03	5.31	0.28	6%
Bridge on Via Matteotti	4.48	4.25	0.23	5%
Via 4 Novembre	3.35	3.43	0.08	2%
Via Massarenti	4.72	5.38	0.66	14%
Via Augusto Righi	4.45	4.72	0.27	6%
Via Andrea Costa – East dir.	4.26	4.79	0.53	13%
Via Andrea Costa – West dir.	4.26	4.99	0.73	17%

2. Method and Data

The paper presents a case study applied to the city of Bologna, where approximately 270,000 GPS traces of bicycle trips were recorded from April to September 2017, thanks to the 'Bella Mossa' campaign. This database also provides information about cyclist's age and gender. 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. The analysis consists of three different phases: 1) Evaluate cyclist's in-motion speeds from the GPS data sample and match them to the network edges; 2) Validate the algorithm that estimates in-motion speeds from GPS traces and test the database representativeness; 3) Analyse the results derived from the application of the algorithm to the GPS database. The first analysis has been performed by means of the software Sumopy (SUMOPy (2021)) and the use of network data from OpenStreetMap OSM (2021), as explained in Rupi et al. (2020). A pre-processing filter unsuitable GPS traces, match the remaining tracks to the transportation network and filter the wrong matched trips. In this way, GPS traces out of the study area or with bizarre length, duration or speeds are discarded, as well as not-matchable traces: typically, many traces cannot be map-matched because no route can be found that follows the GPS points, for example if cyclists ride on the opposite direction of a one-directional road. 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 specific edges, nodes or even maneuvers within intersections. Finally, the cyclist's in-motion speed is evaluated as the traveled distance under the total trip duration depurated from the waiting time. The second phase has been possible by means of a manual survey focused on measuring the average in-motion speeds of casually passing cyclists on a predefined number of road sections by recording the time to cross a known length (between 30 and 40 meters). The survey has been conducted between November 7th and November 18th, 2020, on 17 road sections and during the morning rush hours of weekdays, from 7am to 10am. The in-motion speeds recorded during the manual traffic survey have been then compared with speeds evaluated on same network edges and time interval from the Bella Mossa data sample. The road sections were chosen to represent the entire array of infrastructure types within the study area and between the most used bikeways (see Rupi et al. (2019)); also, the road slope on these sections, as well as in the vast majority of the streets of the urban network of Bologna, is negligible. Finally, the last step requires a post-results elaboration, which consists of grouping in-motion speeds per cyclist categories and road typology, in order to observe what may condition the cyclist's in-motion speeds.

3. Validation analysis

The monitored sections and the measured and estimated values from the GPS data sample of the in-motion speed of cyclists are shown on table 1. On average, the relative difference between estimated and measured speed on the monitored sections has been less than 8%; in over 70% of cases the percentage difference has been less than 10%, whilst the maximum percentage difference has been 17%, pointing out a good correspondence among measured and estimated average in-motion speeds. The results of the linear regression between measured and estimated in-motion speeds are reported in figure 1. It emerges a good enough correlation (R2=0.76), considering that there is a temporal offset of three years between the measured and estimated values. The coefficient of the interpolation line and the constant term are close to 1 and 0, respectively, indicating a good estimation of in-motion speeds. Furthermore, also considering the results of other validations on gender and age composition (see Poliziani et al. (2020)), it is also possible to conclude that the GPS data sample represents well the cyclist's population.

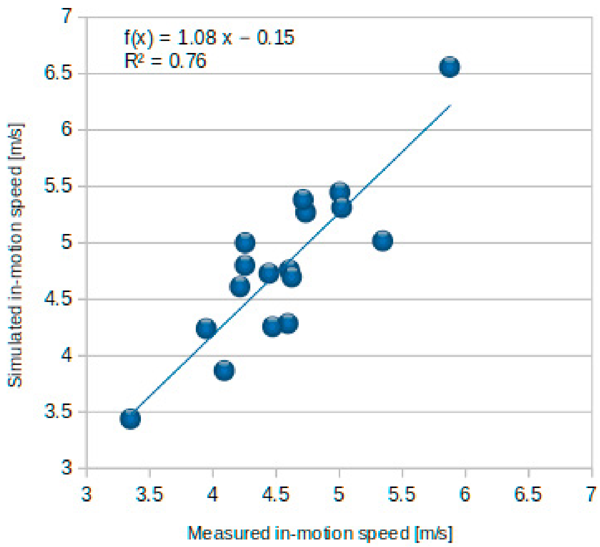

Fig. 1. Measured versus simulated in-motion speed - algorithm validation and test of data sample representativeness

4. Data elaboration and main results

As the pre-processing is composed by many filters, and only high-quality GPS traces are required to estimate cyclist's speed profile, the final sample is composed of 105,000 GPS traces, and approximately 12,400 have been recorded during the morning rush hours on weekdays. Successively, the study has focused on analyzing how in-motion speeds depend on infrastructure elements and cyclist's personal attributes. The analysis has been performed in two different ways: with all GPS trips and only with trips during the morning rush hours. The average in-motion speed of cyclists has been on average 4.7m/s, 30% higher than the average speed, and figure 2 reports bars indicating the first, second and third quartiles, as well as the minimum and maximum values - considering a maximum Whisker length of 1.5 times the interquartile range – of in-motion speeds recorded by cyclists of different categories based on age, gender and biking frequency. In-motion speed of male cyclists is on average approximately 11% higher compared with female cyclists. Cyclists between the ages of 25 and 35 years old are the fastest cyclists: this age group is 2% faster compared with cyclists of ages below 25 years and cyclists between the age of 36 and 55 years, while they are 7% faster compared with cyclists older than 55 years. It is worth noting that the average in-motion speed of cyclists is 2.5% higher during morning rush hours, respect to the whole day, thus indicating that cyclists do not suffer from traffic congestion. In particular, women increased the average in-motion speed of 3.5%, while men increased their in-motion speed by nearly 2%. The increase of travel speed during the rush hours can be observed with same magnitude for all the cyclist's categories reported in figure 2, therefore, only the results related to all trips recorded during the study period are shown for these categories, while the 'Rush' box regards all trips recorded during the morning rush hours. Also, frequent cyclists – who recorded at least 150 trips during the study period – are 5% faster than infrequent cyclists – who recorded less than 50 trips during the study period. Observing the cyclists' in-motion speed recorded on different road types, cyclists are on average significantly faster on larger roads, longer road stretches, roads with more lanes, and roads with higher priority and tertiary roads (see figure 3). In particular, cyclists riding on roads wider than 5 meters run on average 5% faster than on roads with a width between 2 and 5 meters, and 11% faster than roads narrower than 2 meters. Also, cyclists traveling on roads longer than 100 meters run on average 10% faster than on roads with a length between 50 and 100 meters, and 27% faster than roads shorter than 50 meters, where the outgoing and incoming intersections affect cyclist speed. Observing the number of lanes of the traveled roads, cyclists traveling on roads with at least three lanes run on average 3% faster than on roads with two lanes, and 13% faster than roads with only one lane, where cyclists need to interact more with vehicles: parked vehicles along the one-lane roads and interactions with pedestrian can affect more cyclist's speed, especially in the city of Bologna, where there is often a low visibility of pedestrians who want to cross the road due to the porticoes, which characterize the city. Regarding the road priority, which ranks the network edge in order of importance (from 1, corresponding to local road, to 10, corresponding to highway), cyclists traveling on roads with a priority equal to seven run on average 10% faster than on roads with a priority equal to four, and 14% faster than roads with a priority equal to one. Finally, on tertiary roads, in-motion speeds of cyclists have been 10% higher than on bikeways and residential roads and 15% higher than on footroutes. The figure has been built only with 4,761 edges – about 14% of the total network edges – used by at least 50 cyclists, in order to consider only representative average in-motion speeds on edges, since they vary significantly between cyclists. In this regard, see figure 4, where the stacked in-motion speed absolute frequency distribution recorded on some edges high-traveled - by cyclists is represented. However, also varying the minimum number of 50 cyclists per edge does not significantly change the results. From this analysis, it emerges that cyclist are faster on bigger roads, despite sharing the roadway with motorized vehicles, respect to exclusive cycleways which is in contradiction with previous studies (see Iacono et al. (2007); Clarry et al. (2019)). Probably (fast) motorized vehicles can be seen as a "push" factor, at the cost of increase the personal risk, similar to Thompson et al. (1997).

5. Discussion and Conclusion

A recently proposed algorithm that estimates the cyclist's in-motion speeds from GPS traces and matches these to specific infrastructure elements (see Rupi et al. (2020)) has been validated and applied to a large sample of GPS traces, after successfully testing the big data sample's representativeness. A manual survey has allowed to measure the average in-motion speeds of casually passing cyclists, which have been compared with speeds evaluated on same network edges and time interval from the Bella Mossa data sample. Results have shown a good correlation between

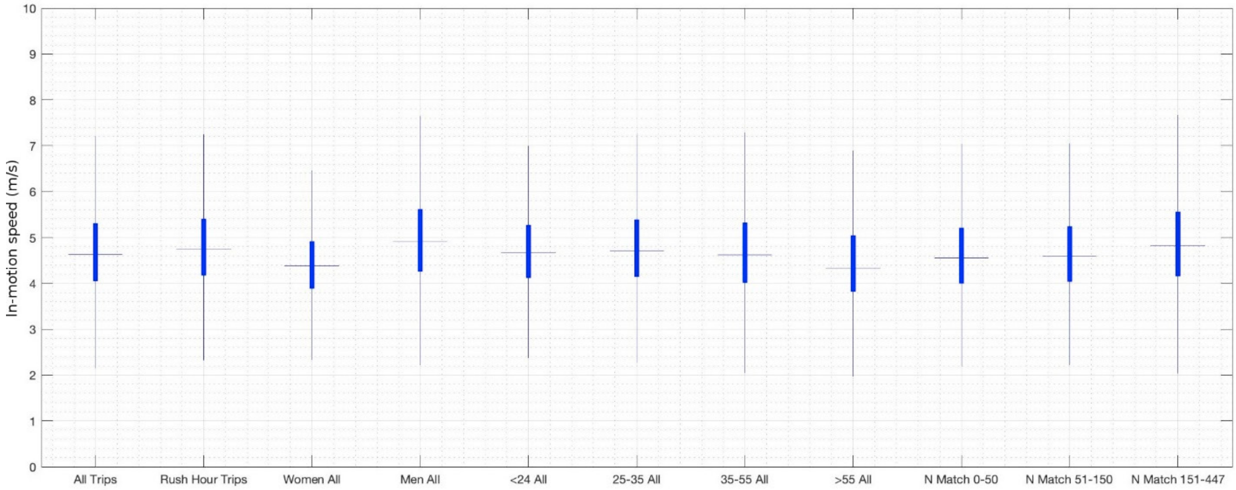

Fig. 2. Cyclists' in-motion speed distribution for different cyclist typologies

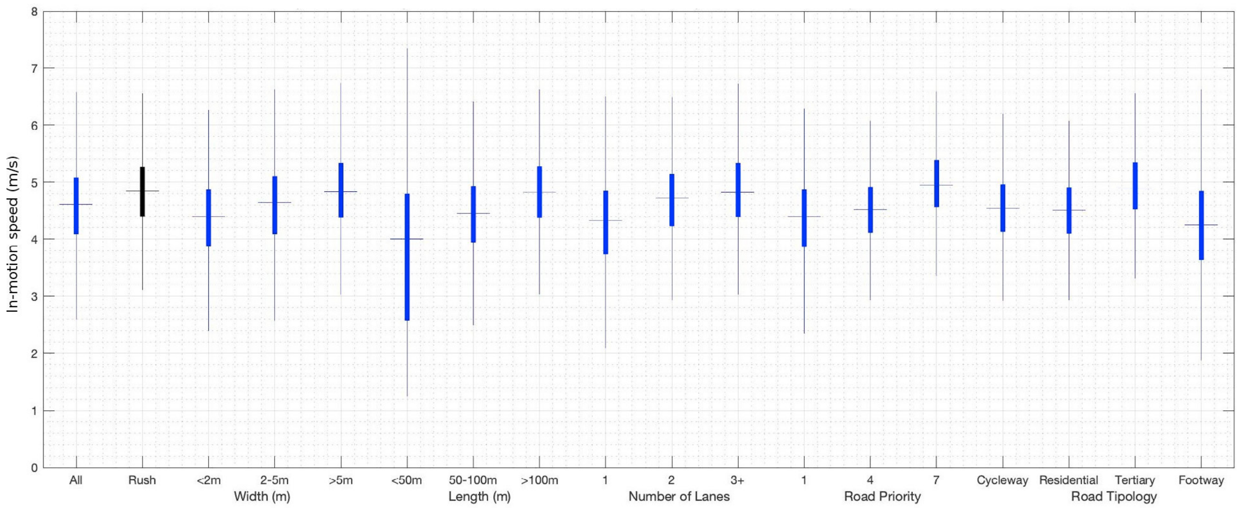

Fig. 3. Cyclists' in-motion speed distribution for different road attributes

measured and estimated in-motion speeds. Once the algorithm has been validated, the study has allowed to analyze how the in-motion speeds obtained by applying the algorithm to the GPS database depend on infrastructure elements and cyclist's personal attributes. Cyclists in-motion speed is on average 4.7m/s, 30% higher than the average speed. The most interesting results are that average cyclist's travel speed increases with road width, number of lanes, road length and road priority. Highest average speeds have been recorded on larger roads shared with vehicles and these speeds are even greater than those on exclusive and separated cycleways, where there is no interaction with vehicles. Moreover, the average in motion speeds recorded on segregated cycleways and residential roads are similar, and higher than those obtained for footpaths, where interactions with pedestrians often force cyclists to slow down. Male cyclists record on average an 11% higher speed than women, and faster cyclists are of an age between 25 and 35 years. Frequent cyclists are 5% faster than infrequent cyclists. Another interesting aspect is that cyclists even increase the average in-motion speed during rush hours by about 2%, without being affected by traffic congestion. As conclusion from the results, it seems the higher the interaction with motorized vehicles the higher the cyclist's speed; the presence of motorized vehicles seems to be perceived as a push-factor for the cyclist, at the cost of an increased personal risk. Results can be useful to apply the validated algorithm to other case studies, to support bike-accessibility estimation, thus improving cycling conditions has consequences in terms of equality: in this regard, transportation policy or

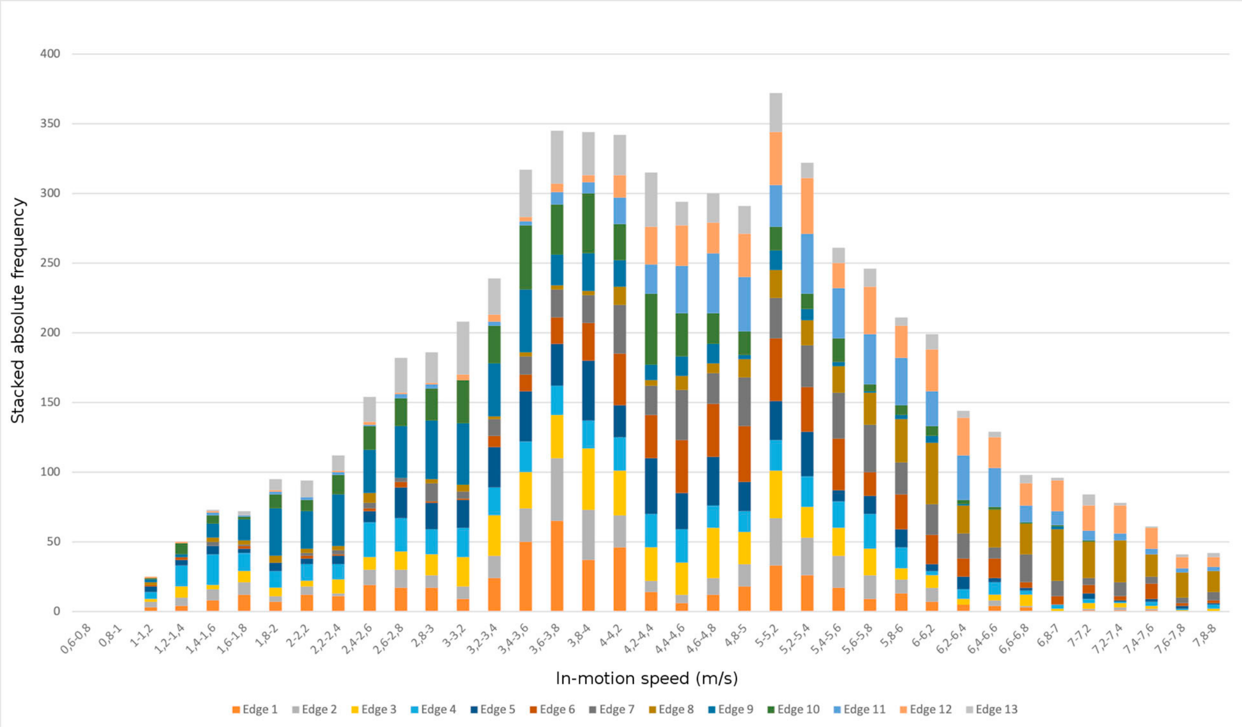

Fig. 4. Stacked frequency distribution of in-motion speeds recorded on some high-traveled edges by cyclists

technology should not only advance the overall accessibility but also improve the least advantaged groups' accessibility levels, narrowing their difference to the average. Also, results can help calibrating cyclist's route choice model and cyclist's dynamics on traffic microsimulations and support the design of an efficient bike-network, which allows to reduce travel time, to increase the cyclist's safety and to facilitate cycling in order to encourage commuters to switch to non-motorized transport.

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