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Bicycle Traffic Volume Estimation Based on GPS Data

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Abstract

All the analytic methods for assessing the safety or comfort of bicyclists in urban area have as a common factor the number of bicycles that enter the system in a certain time interval or an estimate of that. The estimation of the average bicycle volume based on manual and automatic measurements is time-consuming and often require the use of expensive technology. The paper presents a method of estimation based on GPS data from a bike sharing system as a low-cost option for data collection. The analysis was made for the city of Krakow (Poland), using the daily volume of bicycles from 5 automatic counter loops and GPS data from a bike sharing system called Wavelo. Based on the two-factor analysis of variance (ANOVA) and the Tukey post-hoc test, the influence of "localization" and "day of the week" factors on the share of Wavelo bicycles in the entire bicycle flow was estimated. It was shown that examined share is not significantly different between individual days of the week, but changes significantly between analyzed locations. Developed models are characterized by high R^2 coefficients (exceeding 0.90) and the average error of estimation up to 11.5%. The results of the studies show that bicycle volume can be estimated based on GPS data from bike sharing system. However, it is necessary to carry out control measurements to verify developed models and their possible application in other locations.

Keywords: GPS; bicycle; volume; bike sharing system

1. Introduction

In the last years, a lot of actions were done in Poland to promote the bicycle as an attractive and alternative to motorized transport mode (e.g. new bicycle infrastructure facilities were built, the standard of the existing

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infrastructures is constantly increased, different cities implemented bike sharing systems). As a result, the bicycle is a much more popular mode of transportation. Therefore, a new and wider view on bicycle traffic and cyclists' safety is needed. Additionally, the growing needs of cyclists, when planning and designing bicycle infrastructure, have to be included.

The main characteristic of bicycle traffic is its volume. In opposite to motorized traffic, bicycle volume data is difficult to obtain. The reason is that cyclists volume is strongly affected by the presence and standard of bicycle infrastructure, motorized vehicles (including traffic volume, vehicle speeds, the share of heavy vehicles), weather conditions, etc. As a result, parameters of bike trips (e.g. volume, speed) can change rapidly in different locations. Unfortunately, automatic counters are used very rarely. For example, the first 5 automatic counter loops were implemented in Krakow in 2016. Bike trips can be made on the roadway, sidewalk, bicycle infrastructure, where the implementation of automatic counters is difficult. On the other hand, manual measurements are time-consuming and require adequate data of daily, weekly and seasonal variability of bicycle volume. When this type of data is not available, results of short-term measurements cannot be used to estimate e.g. daily volumes.

Difficulties described above, caused needs to search new, more effective methods to estimate bicycle volume. GPS technology is one of the methods very popular in the last years. This type of data, from mobile apps, were used e.g. in: Jónasson, Á. et al. (2013) or Strauss, J., Miranda-Moreno, L. F. and Morency, P. (2015) or Chen, C. et al. (2017).

The paper presents a method of bicycle volume estimation based on GPS data from a bike sharing system as well as an assessment of the relationship between observed bicycle volume from bike sharing system and bicycles in general. The analysis of data from 5 automatic counters located in Krakow and GPS data from a bike sharing system called Wavelo were conducted. The influence of two factors i.e location and day of the week, on the share of Wavelo users in whole cyclist flow, were estimated. The research is an introduction to more complex analysis for the variability of bicycle volume and possibilities of its estimation.

2. Literature review

2.1. Methods of bicycle volume estimations

The most common method of bicycle volume estimation is short-term manual measurements, which are multiplied by daily, weekly and seasonal bicycle volume variability coefficients.

In research carried out in Montreal (Miranda-Moreno, L. F. and Nosal, T., 2011), bicycle volume variability profiles were developed based on data from 5 automatic counters operating in the city. Coefficients from automatic counters were also used e.g. in the analysis of cyclists' accident risk in Los Angeles (Liggett, R. et al., 2016) and design of bicycle and pedestrian traffic monitoring program in Blacksburg (Virginia, USA) (Lu, T. et al., 2017). The coefficients of variation of bicycle volume were taken from national surveys in research on cyclists' safety in the Netherlands (Schepers, J. P. et al., 2011.) and Sweden (Kröyer, H. R. G., 2016). The average daily bicycle volume was calculated based on coefficients from New Zealand (Beca Pty Ltd, 2013) for developing accident risk estimation models at Queensland, Australia. The authors of the report stated that it is not known to what extent these factors are adequate to estimate the bicycle traffic volume in Australia.

The aim of the Amoh-Gyimah, R., Saberi, M. and Sarvi, M., (2016) work was to develop accident models for vulnerable road users in Victoria, Australia. Average daily bicycle volume was obtained for measurements carried out throughout the entire state. The measurements covered only the main routes of the road network. Bicycle volume on other road sections was calculated on the basis of socio-economic data, i.e. the share of bicycle trips to work in the total number of trips for this purpose.

Estimation of accident risk for different types of bicycle infrastructure was the subject of Minikel, E., (2012) research. Due to the lack of detailed cyclists' volume data, the author used results of 2-hours manual measurements of bicycle volume during the afternoon peak hours. The author decided that the comparative character of the analysis (determining relative accidents crash rate) allows using of such simplification. Another method was used in Michigan, USA (Gates, T. J. et al., 2016). Due to the lack of data on pedestrian and bicycle volumes for the whole state, Safety Performance Functions (SPF) were developed based on the volume of vehicles only.

2.2. GPS data in cycling analysis

In recent years methods based on GPS technology have become increasingly popular in traffic volume estimations, including bicycles. Compared to manual measurements and automatic counters, GPS technology allows collecting in a short period big data of traffic, Additionally, not only for single short road section but through the entire trip. This method requires the transport mode to be equipped with a GPS recorder. GPS data can be also obtained from mobile apps, such as Strava or Endomondo.

In bicycle traffic analysis, GPS data was used the first time in 2007 (Harvey, F. and Krizek, K., 2007). The aim of the research was to determine the model of cyclists' route choice including the influence of bicycle infrastructure. The analysis was based on 938 bike trips made by 51 volunteers. Similar research was carried out in Zurich (Switzerland) (Menghini, G. et al., 2010) and Portland (Oregon in the USA) (Broach, J., Gliebe, J. and Dill, J., 2011), (Broach, J., Dill, J. and Gliebe, J., 2012), based on approximately 2,500 and 1,500 bicycle trips respectively.

For the first time, the mobile app was used to obtain GPS data of bicycle trips in 2010 in Los Angeles (Reddy, S. et al., 2010). Since then, many similar applications have been created e.g. in San Francisco (Hood, J., Sall, E., and Charlton, B., 2011), Austin (Hudson, J. G. et al., 2012), Madrid (Romanillos, G. and Zaltz Austwick, M., 2016).

In 2013, data from Strava was used to create heat maps of bicycle volume and analysis of the cyclist's route choice in Reykjavik (Jónasson, Á., et al., 2013). Data from Strava was used to estimate the relationship between Level of Traffic Stress (LTS) and the frequency of accidents with cyclists and their severity in New Hampshire (USA) (Chen, C. et al., 2017).

GPS data of bicycle traffic was also used in models of cyclist route choice (Zimmermann, M., Mai, T. and Frejinger, E., 2017), safety analysis and estimation of bicycle traffic parameters (such as speed, accelerations, delays) (Strauss, J. et al., 2017), (Strauss, J. and Miranda-Moreno, L. F., 2017), (El-Geneidy, A., Krizek, K. J. and Iacono, M., 2007), (Ma, X. and Luo, D., 2016), (Parkin, J. and Rotheram, J., 2010), (Luo, D. and Ma, X., 2017), estimation of bicycle volume (Strauss, J., Miranda-Moreno, L. F. and Morency, P., 2015), analysis of the possibility of using microscopic simulation models of motor vehicles in cycling research (Manar, A. and Cao, G., 2015), analysis of the impact of bicycle infrastructure on the level of physical activity (Dill, J., 2009). The number of bike trips included in those researches ranged from a few measurements of a few hours to over 10,000 observations.

2.3. Bike sharing system data in cycling analysis

Apart from special devices and mobile apps, GPS data of bicycle traffic can be obtained from a bike sharing system. This type of GPS data were the basis for the research on the impact of the system on cyclists' safety and health (Woodcock, J. et al., 2014) and bicycle infrastructure on travel comfort and cyclists' safety (Joo, S. et al., 2015), (Fishman, E. and Schepers, P., 2016). In Washington DC (USA), GPS data from bike sharing system was used to assess demographic and socio-economic differences between cyclists who use the system daily, occasionally and cyclists who not use the system (Buck, D. et al., 2013). In (Fournier, N., Christofa, E. and Knodler, M. A., 2017) this type of data was used to quantify the relationship between bicycle volume and weather conditions, and in (Imani, A. F. et al., 2014) to analyze the impact of land development on bicycle volume.

Bike sharing system in Krakow was analyzed in national research (Łastowska, A. and Bryniarska, Z., 2015). The aim of the study was to calculate variability of trips durations and number of trips in each month, days of the week, time of the day. The authors determined which stations and routes are most often chosen by the bike sharing system users.

2.4. Summary

The simplest and still the most popular methods of bicycle volume estimation are manual measurements. Unfortunately, estimating e.g. daily bicycle volume, based on that data is difficult due to the lack of reliable daily, weekly or seasonal bicycle volume variability coefficients. In the previous research variability coefficients for bicycles were obtained from several automatic counters located in the city, sometimes also in the whole region or country. It should be noted that depending on the function of the road, land development, presence and standard of bicycle infrastructure, the variability of bicycle volume can be different in different locations within one city, not to mention the entire region or country.

The problem described above can be solved by using GPS data from a bike sharing system. However, the assumption that a bike sharing system users are a random sample of the entire population of cyclists, and the traffic patterns of this group of cyclists are related to the characteristics of the entire bicycle flow, has to be made.

The approach is relatively new, inasmuch there are not relevant studies in literature on the estimation of bicycle volume on the basis of the data from a bike sharing system. This method, against the others using GPS data, is characterized by relatively low costs and a more accurate reporting of the travel parameter of all cyclist. There is no need to buy GPS data. Such data may also come from large and popular apps such as Strava. It should be noted that cyclists using this type of apps are often very experienced, and a result may significantly differ from the travel parameters achieved by other cyclists and cannot be a good representative of the cyclists' population.

The aim of the paper was to evaluate a relationship between the volume of all cyclists and those who are bike sharing system users. Such research can give an answer if bike sharing user is a random sample of all cyclists' population.

Calculations were carried out for the city of Krakow, where the bike sharing system, called Wavelo, operates since 2008. The research was carried out in 4 steps: 1) daily bicycle volume from 1st to 23rd June 2017 was collected in 5 locations where automatic counters are available; 2) based on GPS data from bike-sharing system, the volume of Wavelo bicycles was calculated at the locations with automatic counters; 3) ANOVA was used to estimate the impact of two factors, i.e. location and day of the week, on share of Wavelo bicycles in cyclists' flow; 4) models describing the relation between cyclists volume and volume of Wavelo bicycles were developed.

3. Data

Localization of 5 automatic bicycle counters in Krakow is shown in Figure 1. Daily bicycle volumes in those sites are available at the Krakow Road Administration website. Detailed GPS data from the Wavelo system was given by Krakow Road Administration. It was used to calculate the daily volume of bike sharing system users at each of 5 analyzed locations Analysis was made for 3 weeks period of time, (from 1st to 23rd June 2017). The length of the analysis period resulted from the significant amount of GPS data recorded by the system. The analysis period was also chosen to exclude school holidays and public holidays.

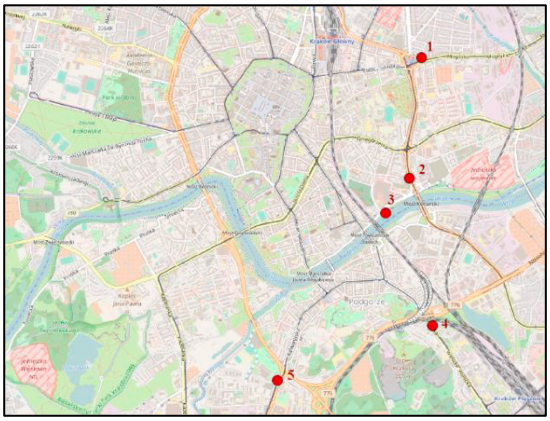

Fig. 1. Localization of automatic bicycle counter in Krakow in June 2017: 1) Mogilska Street, 2) Kotlarska Street, 3) Bulwary Wislane, 4) Wielicka Street, 5) Wadowicka Street.

4. Methodology

The share of Wavelo bikes in the whole cyclist's flow may differ in different locations, days of the week, during schools holidays (comparing to the academic year) and public holidays (comparing to other days). Therefore, it was assumed that if described share, e.g. on weekdays and weekend, is not statistically different for confidence interval equal 95%, then one model describing the share of Wavelo bicycles in all cyclists volume can be developed. Otherwise, separate models have to be determined to reduce estimation errors. Table 1 presents the values of the average share of Wavelo bikes in the cyclists' flow in each location and day of the week. The average share of Wavelo bicycles is around 8%. To assess the impact of two factors: location and week day, on the share of Wavelo bikes ANOVA method was used.

Table 1. Share of Wavelo bikes in the cyclist's flow.

	Sample size	QWavelo/Qall [-]
Location		
1. Mogilska Street	21	0.0621
2. Kotlarska Street	21	0.0774
3. Bulwary Wiślane	21	0.0983
4. Wielicka Street	21	0.0681
5. Wadowicka Street	21	0.0938
Sum	105	0.0800
Day of the week		
Monday	15	0.0776
Tuesday	15	0.0783
Wednesday	15	0.0895
Thursday	15	0.0781
Friday	15	0.0744
Saturday	15	0.0808
Sunday	15	0.0808
Sum	105	0.0800

ANOVA results are presented in Table 2. It shows that observed differences in the share of Wavelo bicycles between each location are statistically significant. However, the analyzed share is similar on all days of the week (no statistically significant differences were observed). There is also no interaction between both included factors (location and day of the week).

Table 2. ANOVA results.

	SS	Df	MS	F	p	Fcrit (p=0.05)
Location	0.020912	4	0.005228	21.999	< 0.001	2.503
Day of the week	0.002028	6	0.000338	1.422	0.214	2.231
Location x Day of the week	0.003301	24	0.000138	0.579	0.937	1.674
Error	0.017152	70	0.000245			
All	0.043393					

ANOVA indicates a significant effect of the location on the share of Wavelo bicycles. To assess which locations are significantly different, a post-hoc Tukey test was carried out. Table 3 shows a comparison of values: the Least Significant Difference (LSD) and the difference between two means (average error values for the estimation of total bicycle traffic volume based on Wavelo system data for the compared locations – xi and xj. In result, the separate model should be developed for both locations 3 and 5. The Tukey test did not give a clear answer on how to develop a model for other 3 locations. Therefore, separate models were developed for locations: 1 and 4; 2 (this model is characterized by the highest R^2 and the lowest coefficient of variation), 3 and 5, and for all the locations.

Table 3. Tukey test results for factor „location"

qα,k,N-k = 3.94		
LSD = 0.0135	|xi – xj|	Differences statistically significant (|xi - xj| > LSD)
Locations 1 and 2	0.0153	Yes
Locations 1 and 3	0.0363	Yes
Locations 1 and 4	**0.0061**	**No**
Locations 1 and 5	0.0317	Yes
Locations 2 and 3	0.0210	Yes
Locations 2 and 4	**0.0092**	**No**
Locations 2 and 5	0.0164	Yes
Locations 3 and 4	0.0302	Yes
Locations 3 and 5	**0.0046**	**No**
Locations 4 and 5	0.0256	Yes

5. Results

Figure 2 presents developed models, i.e. for locations 1 and 4, for location 2, for locations 3 and 5, and additionally for all of 5 locations together.

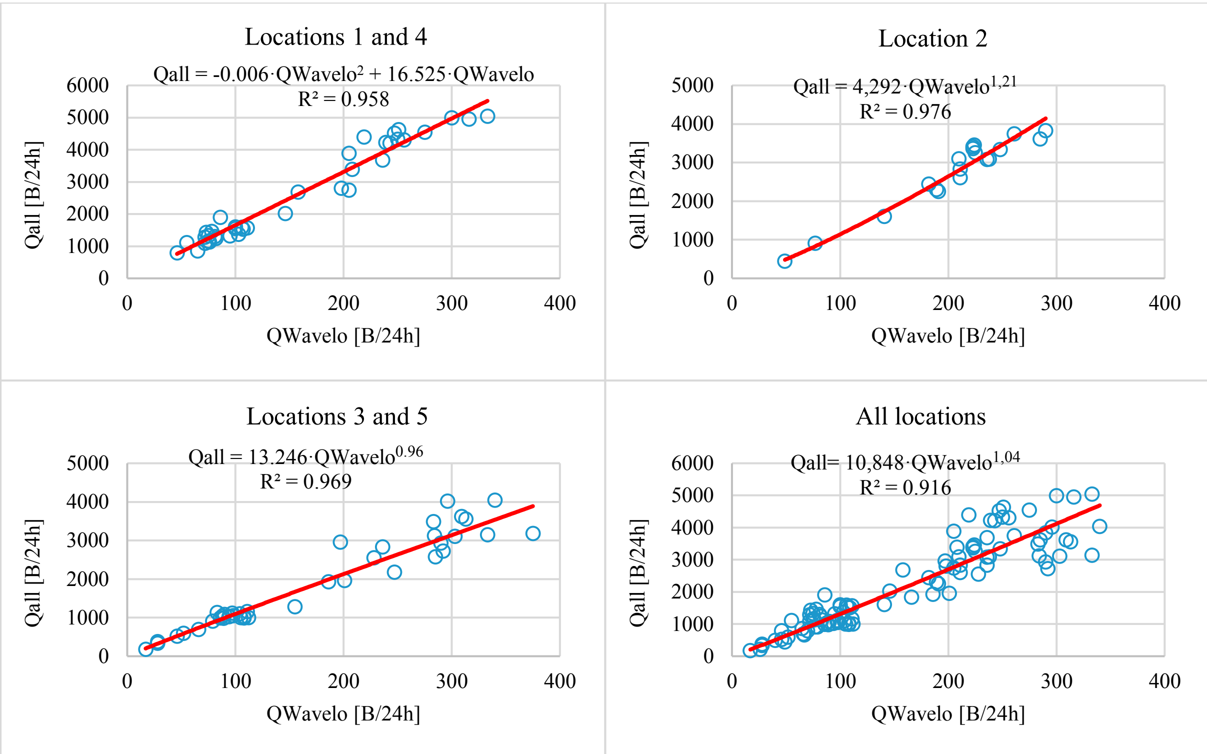

Fig. 2. Models for bicycle volume estimation based on the bike sharing user's volume.

In Table 4 descriptive statistics of each model are collected. Data presented in Table 4 shows that the variability of cyclists' volume is in over 90% described by the variability of bike sharing users volume. The average estimation error differs between developed models and ranges from 7.4% up to 11.5%. The model developed for all 5 locations is also characterized by high R2 (0.916). However, the average estimation error reaches 18%, which is higher in comparison to other models.

Table 4. Models for bicycle volume estimation based on the bike sharing user's volume.

	Locations 1 and 4	Location 2	Locations 3 and 5	All locations
Type of the model	$a \cdot {Q_{wavelo}}^2 + b \cdot Q_{wavelo}$	$a \cdot {Q_{wavelo}}^b$	$a \cdot {Q_{wavelo}}^b$	$a \cdot {Q_{wavelo}}^b$
a	-0.0062	4.2919	13.2457	10.8479
b	16.5255	1.2122	0.9587	1.0413
Sample size	38	19	40	99
R^2	0.958	0.976	0.969	0.916
Average estimation error [%]	0.115	0.074	0.104	0.178
σ	0.066	0.033	0.078	0.121
υ	0.570	0.452	0.757	0.680
Min estimation error [%]	0.002	0.006	0.003	0.001
Max estimation error [%]	0.278	0.124	0.299	0.472

where: R^2 – coefficient of determination; σ – standard deviation; υ – coefficient of variation.

6. Conclusions and future perspectives

In the paper, the relationship between the volume of all cyclists and volume of bike sharing users was analyzed. The analysis was made using data from 5 automatic counters located in Krakow and GPS data from bike sharing system, Wavelo. Based on ANOVA, the impact of location and the day of the week was analyzed. It was shown that the share of Wavelo bikes in cyclist flow is around 8% and does not dependent on the day of the week. However, it differs statistically significantly between analyzed locations. This may be due to the e.g. function of the street and density of the Wavelo station at the surrounding area. As a result of the research, models to estimate bicycle volume were developed. Models are characterized by a high coefficient of determination (>0.90). The results indicate that GPS data from a bike sharing system are really promising in estimating the cyclist's volume in general.

The paper is the first step to more complex analysis of variability of bicycle volume. It is necessary to carry out an extensive validation through control measurements verifying the developed models together with the research on the influence of street function and characteristics of the surrounding area on analyzed dependencies.

The share of bike sharing users in cyclists flow may change during the day and therefore it is necessary to conduct study also in relation to hourly bicycles' volumes. It can also change during the year, for example during school or public holidays. This type of analysis was not yet included in the paper. Cyclists' volume estimation based on bike sharing users volume allows for simply estimation of cycling traffic at any location in the street network with limited costs.

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