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Design, Implementation and Testing of a New Multi-Sensor Mobile Device as a Tool for Cycling Data Collection in Highly Congested Urban Streets

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Abstract

The number of bicycle riders in New York City (NYC) has been increasing steadily in the past few years. These numbers include private and shared bicycles. The NYC bicycle network has been expanded to accommodate the needs of the increasing number of riders. Although the new infrastructure has reduced the number of cyclists killed or seriously injured (KSI) in some areas, in other areas similar improvements were not observed. A data-driven approach to study the possible effects of this type of infrastructure inconsistency on the variation of the number of bicycle crashes from one region to another in the city is the primary motivation of this paper. A highly portable and inexpensive sensing device for measuring the distance between a bicycle and lateral objects is designed and developed from scratch. The developed mobile sensing device can also map bicycle trajectories to highlight critical segments where the safe distance from passing vehicles is not respected. This mobile device is powered by a portable power source and it is comprised of two ultrasonic sensors, a Global Positioning System (GPS) receiver, and a real-time clock (RTC). The sensor is secured inside a custom design 3D printed case. The case can be easily attached to any bicycle including shared bikes for testing. The final prototype is entirely functional and used to collect sample data to demonstrate its effectiveness to address safety-related problems mentioned above. Finally, a dashboard is created to display collected key information. This key information can be used by researches and agencies for a better understanding of the factors contributing to the safety of bicycle routes.

Keywords: *Ultrasonic sensor, Bicycle safety, Traffic, IoT*

1. Introduction

Many cities throughout the world have been investing in bicycle infrastructure to improve the safety of bicycle routes due to the increasing importance and potential of biking as an alternative mode of urban transportation. In New York City (NYC), daily bicycle ridership has increased by 70% between the years 2011 and 2016. The average annual growth rate of daily cycling for the same period was 11.2% [1]. Biking has become an important part of commuting as bicycle routes and shared bicycle stations have been dramatically expanded in the city. Currently, NYC has more than 1,100 miles of bicycle lanes [2]. Although there have been significant improvements in the city regarding bicycle facilities, they do not cover the whole city. For example, the neighborhoods that are further from Manhattan have minimal to no bicycle infrastructure.

Seven districts in Brooklyn and three in Queens are considered priority bicycle districts by the NYC Department of Transportation (NYCDOT) [2]. Each of these districts has a high KSI with either medium or low coverage of bicycle facilities. The areas with the highest number of bicyclists killed or seriously injured (KSI) in 2016 were in Brooklyn and Queens. Both boroughs have fewer protected and conventional lanes than Manhattan. NYCDOT [2] has also identified the categories of crashes responsible for the highest number of cyclist fatalities: cyclist traveling adjacent to a motor vehicle (29%), a cyclist traveling at a right angle to a motor vehicle (27%), and collisions with turning motor vehicles (21%). These fatalities happened mostly at intersections (65%). Based on the types of crashes, one might assume that districts with higher bicycle network coverage would have a lower KSI, and vice versa. However, this is not always the case. They might not always present positive or negative correlations [3, 4]. There are districts that have even fewer bicycle facilities than these priority bicycle districts, but they have a lower KSI [2]. These circumstances raise questions about how these facilities and human behavior influence the overall safety of cyclists in the city.

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Many factors can influence why some regions are safer than others. Some studies relate cyclist safety to the number of cyclists on the road (Jacobsen [5] and Bhatia and Wier [6]). Other studies relate it to the street infrastructure (Allen-Munley et al. [7]) or to the distance between the bicycle and moving/parked vehicles (Shackel and Parkin [8] and Walker [9]). Many states have laws that require motor vehicles overtaking bicycles to maintain a safe distance of 3 ft. In New York City, there are no specific legal restrictions for vehicles overtaking bicycles [10] but there is a recommendation for cyclists to maintain a safe distance of 3 ft from parked vehicles [11].

With the help of disruptive technologies in transportation, newer and more intelligent sensing systems are being deployed in motorized vehicles [12]. While the advancements in mobile wireless communications and the Internet of Things (IoT) technologies have made connectivity between various elements of the transportation system possible, non-motorized modes have not received as much attention. Most of the technologies designed for intelligent vehicles can be modified for use with non-motorized transportation modes. However, there are not many studies in the literature providing insights into bicycle and bicyclist dynamics utilizing intelligent sensors. Part of the reason for this is due to the unavailability of on-board power, which can be solved with the use of portable power chargers. The introduction of e-bikes might also solve this issue, as their battery can be used to power the sensors.

There is an increasing need for the development of new unobtrusive and low-cost technologies to help improve data collection for research that focuses on promoting the safety of bicycle users. With the proliferation of IoT devices, sensors, and open-source information, it is now possible to develop devices that address different challenges of the data collection process. In addition, data visualization tools have improved with the advance of technology. Using dynamic dashboards to consolidate the key information from data sets in one screen allows users to conveniently run analysis and draw conclusions using the presented data.

Our main objective is to use emerging mobile sensing and other technologies to improve the safety of bicyclists in urban environments. We hope to achieve this overarching objective via three distinct and challenging goals. The first goal is to use the developed mobile sensing device to identify hotspots where vehicles operate dangerously close to the bicycle. This information is expected to help identify high-risk street segments for cyclists. The second goal is to compile a comprehensive bicycle safety dataset including real-world bike trajectories, unsafe distances, speed and acceleration measurements for the existing infrastructure. The final goal is to create a device that will alert bicyclists when they might be in a dangerous situation.

This paper mainly focuses on our first goal of developing an integrated, inexpensive and highly portable multi-sensor mobile device as well as an accompanying customized software platform for collecting and processing bicycle safety data and a dashboard for the visualization of key performance indicators. The multi-sensor mobile device can collect bicycle trajectory data and lateral distances between the bicycle and objects around it. It is built using ultrasonic sensors connected to a Raspberry Pi (RPi) to measure the distance between the bicycle and lateral obstacles, especially moving vehicles. RPi is a single board computer using a Linux based operating system, and it is widely used in research projects in the literature (Miha [13], Dozza et al. [14], Ambrož [13], Kurkcu and Ozbay [15], and Kurkcu, Ozbay [16]). Fig. 1 shows how the bicycle is usually positioned on the road and a representation of ultrasonic sensor measurements.

2. Background

The number of studies concerning bicyclist safety has significantly increased in recent years. They range from identifying the factors that influence the number of incidents involving bicyclists, to new technologies deployed to improve the data collection and overall experience of the bicyclist. Most of these bicycle safety studies have mainly used the data available from surveys, police crash reports, and simple video observations. Their efficiency can be improved by making the data collection process faster, inexpensive, and more ubiquitous and reliable. For example, Laureshyn, Goede [17] used video processing to evaluate accidents involving cyclists at intersections in Norway. They compared three different models by how they quantify and identify the frequency of the accidents by type. Their results show that the models have great potential as tools for identifying unsafe interactions. Nonetheless, more data is needed to validate these models. A possible solution for acquiring more reliable data is the use of multiple sensors for continuous data collection. Dozza and Fernandez [18] implemented a device using multiple sensors to collect cycling data. The study presented a methodology similar to that used for naturalistic driving data for motor vehicles. They collected data including video, acceleration, directional vector, angular rate, latitude and longitude, heading, velocity, and pressure on the brake, which was used to understand the behavior of cyclists and bicycle dynamics.

The ridership of traditional bicycles is increasing at a considerable rate with the introduction of new bicycle sharing systems, which leads to concerns of the interaction of these systems with the existing traffic [19]. In addition, the introduction of e-bikes has brought up new considerations in bicycle safety studies. The e-bikes can reach higher speeds and enable longer rides. Therefore, they increase the probability of accidents involving cyclists [19,20]. To understand the differences between the bicyclist behavior and dynamics of traditional bicycles and e-bikes, Werneke and Dozza [21] and Dozza [20] created two systems called BikeSAFE and e-BikeSAFE to collect naturalistic cycling data from traditional bicycles and e-bikes. They identified that the collection of data from e-bikes is still not as efficient as on traditional bicycles. The development and enhancement of systems like e-BikeSAFE can provide valuable data to address the unique issues of e-bikes.

A significant example of how such sensors could help with e-bike safety is the latest problem faced by Citi Bike. The company announced that it would expand its fleet with 4,000 pedal-assist e-bikes on February 28th, 2019. Shortly after the announcement, they reviewed a small number of reports from riders who experienced hard braking problems on the front wheel [22]. The New York Daily News [22] reported that one user flipped over the handlebars and broke his hip. The newspaper also confirmed at least four other people received medical treatment following incidents involving hard-stopping front brakes. However, it is still not clear whether the reason for such incidents is hard braking [23,24]. If pedal-assist e-bikes had embedded smart sensors, it would have been possible to identify the actual reason for these incidents by analyzing collected data from the bicycles.

Strauss, Zangenehpour [25] addressed deceleration/braking and its relationship to cyclist safety in their study. They used smartphone GPS data to correlate the deceleration rate of traditional bicycles to the number of injuries observed at intersections and along with segments of the road. They showed that the deceleration rate has the potential to be used as a surrogate safety measure. Although smartphone GPS data was used to get the deceleration rates, it can have lower accuracy in dense urban environments. A combination of multiple sensors can expand the safety of all users on urban transportation networks [26].

Sensors can not only be used to record data for later analysis but also to perform real-time analysis of various data sets [27,28]. A multiple-sensor system can be used to collect real-time data and process it to warn the bicyclists of possible dangerous situations. For example, it can identify a failure in the brake system or if the bicyclist is hard braking and warn the bicyclist to prevent an accident from happening. Liebner, Klanner [29] used a similar methodology to deploy a warning system for drivers. They use a smartphone GPS to continuously send the location of the bicycle to the warning device on the vehicle. The device uses that information to alert the driver in case of possible dangerous interaction. They use a high precision differential GPS to assess the accuracy of the smartphone GPS data.

Other projects have used ultrasonic sensors to measure the distance of motor vehicles overtaking bicycles. However, the size, weight, and cost of the equipment used in these studies are unsuitable for large-scale data collection. Shackel and Parkin [8] and Walker [9] used ultrasonic technology to measure the distance of a bicycle from passing vehicles. The device developed in this project differs from the previous ones because it adds the GPS module, which contributes to the identification of routes and critical points where dangerous overtaking happens. The use of cheaper and smaller components results in a product that is portable and adequate for mass data collection. The data obtained with the device can be used to help identify the locations where drivers get closer to bicycles and investigate if this behavior is related to the type of bicycle facility. Additionally, the mapping of hotspots of dangerous clearance between motor vehicles and bicycles can be combined with the crash data to evaluate the connection between safe distance and the KSI number.

3. Device Architecture

The mobile sensing device prototyped as part of the research described in this paper is primarily designed to continuously measure the distance between two objects. The device is developed to collect lateral distance data with time and space stamps data to help analyze safety-related patterns in terms of lateral distances between bicyclists and drivers operating in different types of bicycle facilities in highly congested urban transportation networks. To achieve this goal, a prototype consisting of multiple sensors was built and attached to a bicycle in NYC. To make the device portable and easy to mount, a special enclosure was designed using the software Fusion 360 and 3D printed in Polylactic Acid (PLA) with an Ultimaker 3 printer. Figures Fig. 1 and Fig. 2 show the multi-sensor mobile device mounted to a bicycle and the components.

The device is built using two ultrasonic sensors, a Real-Time Clock (RTC) and a GPS receiver connected to a low-cost small computer board namely, a Raspberry Pi 2 B v1.2. The ultrasonic sensors used in this study are cost-efficient and can detect a variety of solid objects without being intrusive to pedestrians [30]. The maximum efficiency for this type of sensor is achieved when the pulse emitted is perpendicular to the surface. It can reach a minimum and maximum range of 2cm and 400cm, respectively. The accuracy of the sensors can vary depending on the temperature and humidity of the environment [31].

Fig. 1 - Multi-sensor mobile device mounted on a bicycle

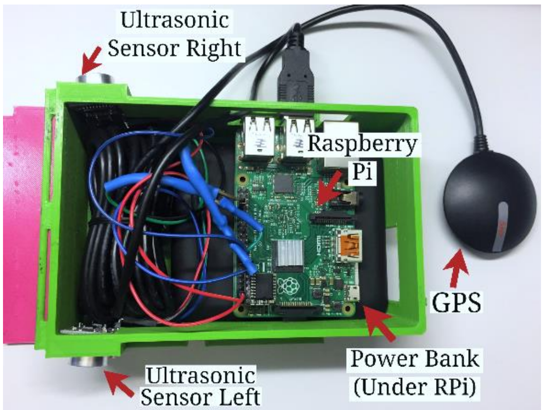

Fig. 2 - Multi-sensor mobile components

The sensing device is charged by a portable dual USB power pack, which has a 2500mAh lithium-ion cell with an output of 3.7VDC. The power pack can charge the device for up to 2.5 hours. The components chosen for building the device were based on their quality, cost, and dimensions. The final prototype dimensions are 11.2 cm by 16.5 cm, and its total cost is around $200.

A Python code was developed by the authors to read the data from the ultrasonic sensors and from the GPS receiver and then combine this data into a single file. The code defines the left and right sensors according to the GPIO pins they are connected to. The differentiation of left and right sensors is needed to identify if the distance read is from moving or parked vehicles. The data from the sensors and GPS are stored in a database file using the library SQLite3. Another SQL table is created to store log messages to keep track of when the GPS is initialized and there are reading errors.

The code is set to run on the device at the RPi operational system startup, and it keeps running in the background as long as the device is powered. The database file is created in the first run of the code and then, for the next runs, the data is added to the existing file. At the end of the data collection period, collected data is transferred to a desktop computer to be post-processed and further analyzed. Fig. 3 shows the sensing device's architecture.

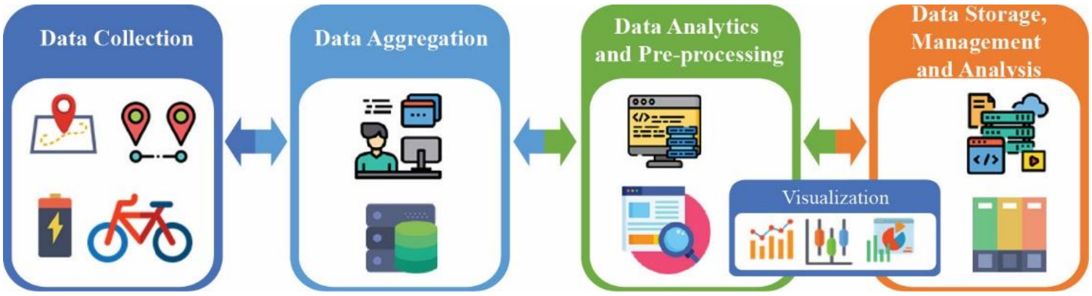

Fig. 3 – Data Architecture of the Developed Mobile Sensing Device

In Fig. 3, the first process represents the collection of the data by individual sensors of the device. The data aggregation process is performed when the data collected is pre-processed and temporarily stored by the device. The final step is to permanently store the data to make it available to the public. The visualization comes after the data analysis process. In the visualization process, the cleaned and processed data is used to create different visualizations for a better understanding of various safety performance measures.

3.1. Data Analytics and Pre-processing

The stored data is transferred to a regular computer for further analysis using a secure file transfer protocol. If sensors have a network connection, this data transfer process can also be executed on-line. This feature allows researchers to remotely analyze and evaluate historical and real-time data.
Currently, the data file is manually imported to a GIS software for data querying, analysis, and visualization. It is post-processed to clean the failed GPS readings, data points that are not part of the route that was actually traversed by the bicycle, or ultrasonic sensor measurements that are out of range or too large due to erroneous readings. The last step is to filter the above-mentioned data points and display the remaining relevant GPS pings on a map.

3.2. Data Storage, Management and Analysis

The final stage is for permanently storing the data and preparing it for final use and presentation. The final cleaned and queried data is stored in the cloud. The defined routes were associated with the characteristics of the available bicycle network and the time of day, such as if a determined trajectory was covered during the rush hour, at nighttime, and over a conventional bicycle lane or not. Finally, initial data visualization is enhanced by formatting and adding features such as legends and scale to the images. The graphs and images containing the main information of the data set are combined in a dynamic dashboard. The dashboard allows the user to see the different data combinations using filters.

4. Cycling data collection and processing

The test route for our multi-sensor mobile device was chosen based on the data of the number of historical crashes provided by the New York Police Department [32]. The data show that one of the streets of the chosen route has the highest number of collisions involving bicycles. The route has segments with protected bike lanes and segments with conventional bike lanes. Some segments of the bike lanes are interrupted by intersections, driveways, work zones, on-street parking spaces, or sections with faded markings. Moreover, even though they are in regions with some tall buildings, the canyon effect does not have a significant impact on GPS readings at this location.
For the preliminary field test, the multi-sensor mobile device is mounted to a regular bicycle. The riders went through the determined route without changing their usual behavior when cycling. The exact time and mileage of each ride were recorded. The start and end times are used to filter the data and group the records collected with the multi-sensor mobile device by each ride. The rides happened in different times of the day. The total distance of the route is of 0.9 miles.
The data was cleaned and filtered by eliminating points with zero latitudes/longitudes and readings of distances over the ultrasonic sensor range (400 cm). Multiple points with speeds of zero at the same location were combined into one. Because the multi-sensor mobile device is mounted on the center of the bicycle's body, the distance from the center of the bicycle to the edge of the handlebar is subtracted from the readings from both left and right ultrasonic sensors.

5. Results and visualization

The performance of the device was satisfactory for each of the processes namely, data collection, data aggregation, data analysis, and data storage. The data set had some null values of GPS readings, which can be justified by the initialization time to get the minimum number of satellites needed by the antenna. The final cleaned and processed data was consolidated in a dashboard to summarize the key aspects related to the bicyclists' safety. The dashboard contains the trajectory of the bicycle and the time series of the speed in mph. Fig. 4 shows a sample of the dashboard with the map representing GPS points and their spatial distributions for five rides performed by the same cyclist. The dark green points on the map represent the record within the safe distance, whereas the red ones are bellow the safe distance of 3 ft.

Fig. 4 - Dashboard platform to visualize and analyze collected mobile data using the developed sensing device

From the dashboard, it is possible to see that the rides had a considerably higher amount of records closer than the recommended safe distance. It is also noticeable that the red points (below safe distance) have lower speeds, which is supported by a Pearson Correlation Coefficient of 0.35 between the distance from the left side and the speed in mph. This coefficient characterizes a moderate and positive correlation. In addition, near misses are identifiable through the collected data by looking at the right and left distance readings, speed time series, and location. For one of the rides, a traffic jam was also identified by a continuous line of points below the safe distance from the left side.

There are 124 records with distance readings smaller than the safe distance for the left side and 181 for the right side. The segment on Jay street registered 53.81% of the total number of occurrences within an unsafe distance from the left side of the bicycle, while Brooklyn Bridge Boulevard was responsible for 3.55%, Livingston street for 22.84%, and Tillary street for 19.80%. Fig. 1 shows a representation of the percentages of records within unsafe distance for each street.

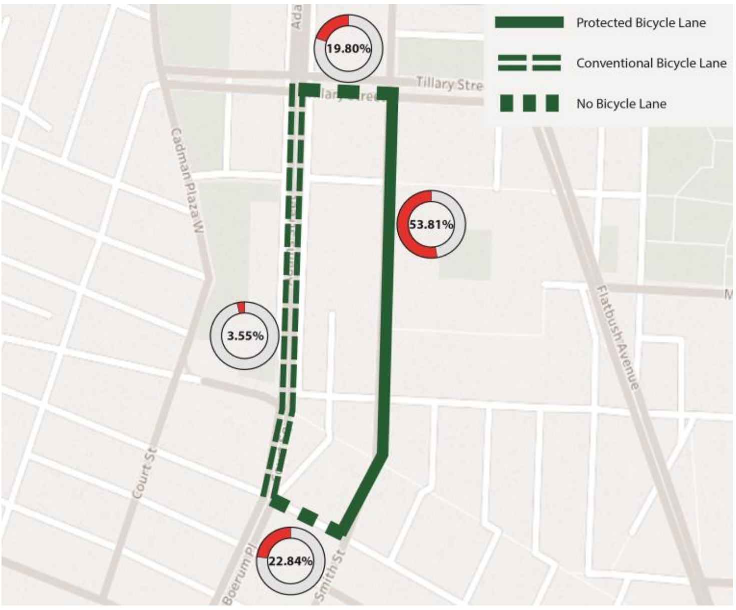

Fig. 5 – Map of percentage of records within unsafe distance

When considering the occurrences within an unsafe distance from the right side of the bicycle, Brooklyn Bridge Boulevard was responsible for 41.85% of the total. Jay street was responsible for 24.68% of the total number of distances within the unsafe distance from the right side of the bicycle, Livingston street was responsible for 20.92%, and Tillary street by 12.55%. The test rides had more occurrences below the safe distance from the right side than from the left side for all the segments.
The average speed was 6.39 mph. For the records with a distance shorter than 3ft for the left side, the average speed was 4.87 mph. Meanwhile, for the right side, the average was 6.86 mph. The records within the safe distance to the left side had an average speed of 7.34 mph, and for the right side, the average was 5.79 mph.

6. Conclusion

A prototype for collecting ultrasonic and GPS data was developed. The device was stable during the data collection process and was able to provide the expected data set necessary for the proposed analysis. The processed data obtained from the mobile sensing device was used to demonstrate how this type of data can be useful for conducting different and detailed safety analysis. The analysis of the sample data showed the points in which the bicycle was within an unsafe distance from parked vehicles and vehicle traffic. In addition, it was possible to identify two potential near-misses and traffic congestion. Finally, the dashboard was successfully implemented as the main visualization tool, and it facilitated the data analysis process.
As the developed mobile sensing device provided good initial results, 3 more units will be built in the near future to be field-tested on bicycles traveling along with different types of routes. Some improvements will be implemented in the future units. First, the size of the multi-sensor mobile device will be reduced to make it portable. Second, a new communication feature will be added to send the data directly from the RPi to a cloud server using a wireless connection. The remote and real-time access to the data will make it possible to create a real-time tracking system to monitor the functioning of the units, observe the behavior of each cyclist and monitor dangerous distances. With the increased sample size, it will be possible to conduct a more in-depth analysis of the factors influencing bicycle safety and to develop new studies after enhancing the device with new types of sensors such as LiDAR and cameras. Tests using the e-bike's on-board power supply to charge the device could be performed to improve the charging of the multi-sensor mobile device.

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