ACCELEROMETER-BASED SURFACE CLASSIFICATION FOR DOCKLESS MOBILITY VEHICLES

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ABSTRACT

The recent popularization of the micro-mobility movement has led to widespread distribution of personal mobility devices in urban centers. These devices, often taking the form of electric scooters or bikes, can be rented by users as an inexpensive, environmentally-friendly, and flexible means of transportation. The volume of devices, coupled with improper usage and lack of regulation, has led to an uptick in accidents, danger to pedestrians, and as a consequence, bans by many municipalities. Clearly, a means of observing and correcting user behavior (particularly with regard to eliminating use in pedestrian zones) would be beneficial. This paper presents a low-cost surface classification tool, utilizing an E-Scooter-mounted accelerometer sensor, which could be used to gain insight into real-time user behavior through the analysis of inertial features. Varied ground surfaces have unique features and textures, which translate into unique data patterns. Our tool extracts such patterns from the acceleration data to make an accurate (94 % accuracy in testing) classification of the surface on which a personal mobility device is travelling, and by extension grants the ability to discern use in allowed/disallowed zones according to surface type.

Keywords E-Scooter · Micromobility · Accelerometer · Classification · Data Science

1 Introduction

The micro-mobility movement has swept across urban centers in recent years, with companies such as Bird and Lime deploying thousands of shared electric scooters ("E-Scooters") onto city streets around the world. These E-Scooters have been quickly adopted as a flexible mode of transportation, used by city residents and tourists alike to get around [11] [3]. In addition to the benefit of convenience to the consumer, E-Scooters also have significant environmental potential — a 63x reduction in carbon emissions per trip compared to a gasoline automobile [2]. This benefit is especially consequential, as the majority of E-Scooter trips would have otherwise been made by an automobile, and not on foot [11].

There have, however, been negative consequences to the rapid deployment of this technology. The large volume of E-Scooters, coupled with a lack of existing regulation and infrastructure, has led to an increase in accidents and danger to pedestrians [12]. Riding on sidewalks, a behavior shown to cause collisions and pedestrian injury [9], is one of the most common complaints of E-Scooter adoption, even in pilot programs with clearly-defined regulations prohibiting sidewalk riding [11]. As a result, many cities and municipalities have banned E-Scooters from riding on sidewalks [4], with some even going so far as to ban the devices altogether [14].

Clearly, E-Scooters are a promising technology in need of some restraining system to identify and respond to where the scooter is being ridden. This challenge of determining environmental positioning is not a unique one, being found also in the fields of robotics and autonomous exploration. Existing solutions utilize a range of sensors and machine-learning classifiers to make inferences about the surrounding environment [13]. These techniques require a relatively large amount of processing power, making them costly to implement, and thus unrealistic to deploy on thousands of E-Scooters.

Our research was initiated in specific response to the ongoing E-Scooter pilot of Santa Monica, wherein disallowed E-Scooter usage zones (most notably, pedestrian sidewalks) bear their own distinctive textural features. For discernment of allowed usage, therefore, it is sufficient to make a binary surface classification of disallowed vs. other. This method could be extrapolated to other geographic locations by re-calibrating the algorithm to accommodate for different sets of disallowed usage zones.

Our solution uses a single accelerometer – a small, low-cost sensor [1] that measures acceleration – and a simple algorithm that can be run on hardware already inside of many E-Scooters [8]. One such accelerometer sensor, mounted to an E-Scooter, collects data from the jolts and bumps caused by riding the scooter across a surface. Distinct surfaces — each with a unique combination of textural features — generate distinct patterns of data that are used to classify the surface, and in turn, the location where the E-Scooter is being ridden. Our proposed system accurately distinguishes between sidewalk and asphalt surfaces with a 94 % accuracy rate and 2 % false triggering rate.

2 Procedure

Our work, carried out over a 10-week span, began with data collection and progressed through the development of a classification algorithm and construction of a physical test platform.

2.1 Test Platform

To carry out our work, a test platform was developed, consisting of three main components: test vehicle, data collection, and data processing (See Figure 1).

For the test vehicle, a Razor E-100 electric scooter (hereafter referred to as the "test scooter") was purchased. This particular model was chosen for its low cost and relative simplicity, with the latter allowing for easy modification. According to the manufacturer's specifications, it has a top speed of 10 miles per hour [7], which is comparable to the 15 mile per hour maximum speed of many E-Scooters deployed in cities [6]. Moreover, this scooter shares the same pattern of pneumatic front wheel and rigid rear wheel that is found on many E-Scooter models, meaning that the interactions between the test scooter's wheels and the ground surface are analogous to those of currently deployed E-Scooter models.

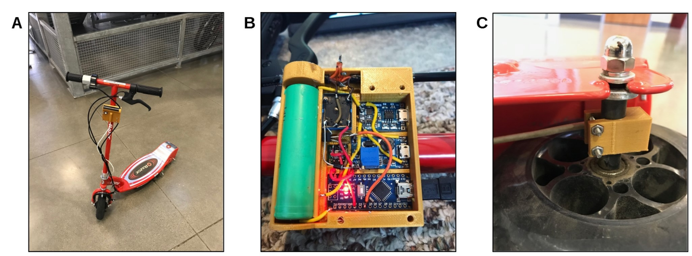


Figure 1: **(A)** Razor E-100 test scooter after modification. **(B)** Arduino Nano, electromagnetic relay, and supporting circuit. **(C)** MX2125 accelerometer sensor mounted to rear axle of test scooter.

For the purpose of data collection, an MX2125 dual-axis accelerometer was mounted to the rear axle of the test scooter. This sensor was chosen for its availability and versatility (large acceleration range, multiple axes of reading, and a breadboard-compatible form factor for prototyping). Our final procedure utilized acceleration data from only one axis, within a +/- 8g acceleration range, indicating that other, more standard accelerometers are compatible with our process, for as little as 0.52 US dollars per unit [1].

For the task of data processing, an Arduino Nano microcontroller was added to the test scooter in order to receive data from the accelerometer, and then in turn execute the surface classification algorithm. This device has less processing power than the microcontroller already inside of popular E-Scooter models [8] [5] [10], meaning that any computational technique detailed in this paper could be readily performed on many E-Scooter models without the need for additional computational hardware.

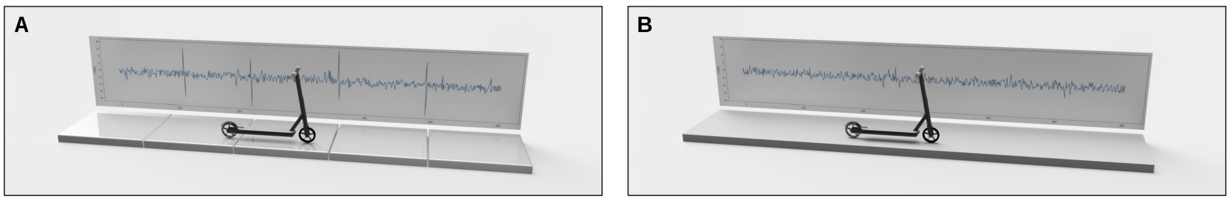
The test scooter's drive system was modified with an electromagnetic relay, so that the onboard Arduino could disable the test scooter's throttle in response to a disallowed surface classification. This feature, while not strictly needed for the verification of our classification system, gave useful feedback during testing and also demonstrated a potential application of our classification technique.

2.2 Classification Algorithm

In the context of our research, the surfaces in need of classification (those representing problem areas of E-Scooter usage, a set labelled "disallowed") were segmented concrete sidewalks and walkways, which bear periodic seams on the surface. These seams, being discontinuities in an otherwise uniform surface, generate inertial features that appear in accelerometer data when a scooter is ridden over them.

These inertial features have characteristic, adjacent alternating peaks, caused by the initial collision and subsequent rebound of the test scooter's wheel with the ground seam. These features are also periodic, as they occur when the test scooter drives over the regularly intervaled ground seams (as shown in Figure 2A).

Figure 2: **(A)** Accelerometer data from sidewalk E-Scooter usage showing inertial features with characteristic double-peak. **(B)** Accelerometer data from asphalt E-Scooter usage showing noise from the surface texture but no inertial features.



Our algorithm evaluates a surface by searching for the distinctive alternating pattern of an inertial feature, and then considering the periodicity of subsequently identified features. If the features recur and the period falls within an accepted range (thereby indicating that the test scooter is being ridden over one of the disallowed surface types), the algorithm makes a positive surface classification. Otherwise, the algorithm returns a negative classification by default.

To search for an inertial feature, the algorithm considers a sliding 15-point window of accelerometer data, which is sampled at 50 hertz. The algorithm identifies the window's maximum positive and maximum negative values and then considers the margin of their predominance. If the maximum positive value is a factor larger than the next largest positive value, it is considered to be a positive peak. This rule is then applied to the maximum negative value. If a window contains both a positive and a negative peak, their adjacency is considered. If the peaks are either adjacent or separated by only one other data point, the algorithm determines that the window under consideration contains an inertial feature.

With an inertial feature identified, the algorithm then considers periodicity among a set of the three most recently identified features. If the time intervals between these features' occurrences fall within an allowed range, derived from the rate of travel of an E-Scooter and the distance between surface features, the algorithm classifies the surface as discontinuous, belonging to the "disallowed" set.

3 Results

Our testing procedure involved riding the test scooter twenty meters over a test surface, at a constant speed of 10 miles per hour. We evaluated our method's performance on four types of surfaces: smooth asphalt, rough asphalt, 36-inch concrete sidewalk (with 36 inches being the distance between seams in the sidewalk surface), and 60-inch concrete sidewalk. We noted false positive classifications (the algorithm returning a "disallowed" classification when the test scooter was ridden on a continuous surface), correct classifications (the algorithm returning a "disallowed" classification when the test scooter was ridden on a segmented surface), and missed classifications (the algorithm not returning a "disallowed" classification when the test scooter was ridden on a segmented surface).

Table 1: Classification Accuracy

	Smooth Asphalt	Rough Asphalt	36" Sidewalk	60" Sidewalk
Correct Classification	96% (24/25)	100% (25/25)	96% (24/25)	92% (23/25)
Missed Classification	N/A	N/A	4% (1/25)	8% (2/25)
False Positive Classification	4% (1/25)	0% (0/25)	N/A	N/A

4 Discussion

Our research was conducted within a broader aim of quantifying and potentially controlling E-Scooter rider behavior, particularly with regard to use on pedestrian sidewalks. In the context of this problem, the accuracy (94% correct identification of prohibited surface types, and a 2% false positive occurrence rate) obtained in our testing demonstrates that an accelerometer-based classification system could be a viable tool for quantification and/or control of rider behavior on certain surface sets. Moreover, due to the low cost of implementation and the compatibility of our process with existing E-Scooter hardware (as noted above), we believe our research demonstrates the feasibility of deploying such a tool on a broad scale.

Many adjustments could be made in order to improve the accuracy and versatility of our classification system. A more sophisticated algorithm could consider dynamic variables such as scooter velocity and rider mass, increasing the robustness of the process. Moreover, to minimize the required computational expense, our algorithm makes a binary surface classification of continuous vs. discontinuous rather than attempting to discern between a large set of individual surface types. While this simplicity allows our algorithm to be carried out by a low power microcontroller without additional computational hardware, it limits the efficacy to regions where allowed and disallowed E-Scooter usage zones present a clear dichotomy of continuous vs. discontinuous. Further research could determine if a more sophisticated classification method can, in fact, be developed within the same computational bounds.

While the aim of our research was to create a classification tool for the quantification of E-Scooter behavior, real-world applications could go a step further and slow or stop E-Scooters that are being ridden on pedestrian sidewalks. E-Scooters are a novel transportation mode with potential to significantly reduce emissions and improve personal mobility; we hope that our work in generating a classification tool will help further their adoption by improving safety, either directly through a hardware solution or indirectly through the adoption of informed policy.

5 Conclusion

Identifying the surface on which an E-Scooter is being ridden could provide valuable data about rider behavior, and even a potential method for directly combating the unsafe behavior of riding scooters in disallowed areas. An accelerometer sensor, reading data from the interaction of an E-Scooter's wheels with the ground surface, can be used as a tool to identify different types of surfaces from their unique inertial features.

To study the application of accelerometer-based surface classification to E-Scooters, a test platform was developed. This platform consisted of an electric scooter, modified with an accelerometer sensor and microcontroller. Testing the platform on different surfaces revealed unique patterns of inertial features on surfaces deemed necessary to classify. Utilizing the occurrence and periodicity of these features, we developed an algorithm capable of identifying such surfaces in real time.

A series of controlled trials were carried out on a number of different surfaces to validate our algorithm. The results of this testing demonstrated that our algorithm was capable of distinguishing between sets of surface types with a high degree of accuracy, labelling them either "allowed" or "disallowed" for E-Scooter usage.

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References

[1] Digi-Key Electronics. *KXTJ3-1057TR-ND Product Overview*. URL: `https://www.digikey.com/product-detail/en/kionix-inc/KXTJ3-1057/KXTJ3-1057TR-ND/6573217`.

[2] Levi Tillemann Lassor Feasley. *Forget the Car. E-Scooters Could Save The City*. Dec. 2018. URL: `https://www.wired.com/story/e-scooter-micromobility-infographics-cost-emissions`.

[3] Craig A Giffi et al. *The changing nature of mobility*. URL: `https://www2.deloitte.com/us/en/insights/deloitte-review/issue-15/automotive-trends-gen-y.html`.

[4] Peter Holley. "Pedestrians and e-scooters are clashing in the struggle for sidewalk space". In: *Washington Post* (Jan. 2019). URL: `https://www.washingtonpost.com/business/economy/pedestrians-and-e-scooters-are-clashing-in-the-struggle-for-sidewalk-space/2019/01/11/4ccc60b0-0ebe-11e9-831f-3aa2c2be4cbd_story.html`.

[5] Parallax Incorported. *Memsic MXD2125 Datasheet*. URL: https://www.parallax.com/sites/default/files/downloads/28017-Memsic-MXD2125-Datasheet.pdf.

[6] Laura J Nelson. *L.A. approves rules for thousands of scooters, with a 15-mph speed limit and aid for low-income riders*. Sept. 2018. URL: https://www.latimes.com/local/lanow/la-me-ln-scooter-vote-20180904-story.html.

[7] Razor. *E100 Electric Scooter*. Mar. 2018. URL: https://www.razor.com/products/electric-scooters/e100-electric-scooter/.

[8] Mike Senese. *Vandals Crack Open Dockless Scooter, Discover Particle Electron Board Inside: Make:* Apr. 2018. URL: https://makezine.com/2018/04/25/vandals-crack-open-dockless-scooter-discover-particle-electron-board-inside/.

[9] N. Sikka et al. "Sharing the sidewalk: A case of E-scooter related pedestrian injury". In: *The American Journal of Emergency Medicine* 37.9 (2019). DOI: 10.1016/j.ajem.2019.06.017.

[10] STMicroelectronics. *STM32F2 Series*. URL: https://www.st.com/en/microcontrollers-microprocessors/stm32f2-series.html.

[11] Portland Bureau of Transportation. *2018 E-Scooter Findings Report*. Jan. 2019. URL: https://www.portlandoregon.gov/transportation/article/709719.

[12] Tarak K. Trivedi. *Injuries Associated With Standing Electric Scooter Use*. Jan. 2019. URL: https://jamanetwork.com/journals/jamanetworkopen/fullarticle/2722574.

[13] Jens Windau and Wei-Min Shen. *An Inertia-Based Surface Classification System*. URL: https://ieeexplore.ieee.org/abstract/document/5509310.

[14] Frances Yue. *Electric scooters: Love or hate them? Here's what you need to know*. Aug. 2019. URL: https://www.usatoday.com/story/tech/2019/08/13/why-scooters-become-popular-and-controversial/1620357001/.