Campus safety and the internet of wearable things: assessing student safety conditions on campus while riding a smart scooter

Devansh Gupta, Wenyao Xu, Xiong Yu and Ming-Chun Huang

Abstract—The campus environments have traditionally revolved around the use of sustainable and practical mobility vehicles such as bicycles, but similar to pedestrians and bicyclists, the students riding smart-scooter are also vulnerable road users and to severe injuries during road accidents. In this paper, we created a ”smart android system”. STEADi, for monitoring the Smart scooter riders. The system uses a Wearable Gait Lab for, a wearable underfoot force-sensing intelligent unit, as one of the main components. The purpose of this system is to help students who are new to using smart scooters on campus to avoid injuries and accidents by alerting the rider about unforeseen conditions. The system provides adequate data for path tracking, Potholes Detection system, and human balancing ability for the Smart Scooter riders. After careful selection of training data, we have been able to integrate a pothole detector system that identifies worse road segments as having potholes. The proposed system is evaluated based on four balance tests on different terrain and with different diverse riding experiences related to the Smart Scooters. The system testing showed that it can successfully detect several real potholes in and around the Cleveland area and is successfully able to alert the riders, including the lesser experienced ones while riding on different terrains for the potential road-related threats.

Index Terms—Smart sensing , Balancing, Android , GPS, Potholes Detection, Accident Prevention, intelligent systems

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2021 IEEE 17th International Conference on Wearable and Implantable Body Sensor Networks (BSN) | 978-1-6654-0362-7/21/$31.00 ©2021 IEEE | DOI: 10.1109/BSN51625.2021.9507033

1 INTRODUCTION

The easiest way to describe a scooter is a bike without a pedal, seat, and chain. The needed momentum required by a common scooter can be applied by pushing the ground backward but a Smart scooter uses a battery and a motor to maneuver the scooter after the initial push. The main challenge with a scooter is balancing and falling left and right. The scooter exhibits several interesting properties that enable one to maintain balance. The pushing, twisting, redefining of the center of pressure and mass flow mechanisms give conceptual understanding to how systems balance [4].

Recently, Smart Scooter company, Bird, conducted a study on scooter safety. The study concluded that scooters involve similar risks as bikes and other small personal mobility vehicles. As per the report in 2017, the bikes related emergency department visits topped, 59 visits per 1 million miles cycled. Based on the data gathered solely by Bird scooter riders, 38 injuries per 1 million miles was reported by the company. On the contrary, the study also found an interdependence between scooter and bike riders. The cities having higher “People for Bikes” safety scores, reported fewer Bird injuries, concluding cities that make cycling safer makes scooter riding safer, too. Cagdas Karatas et al. showed how wearable devices can be used to enable activity recognition of unsafe driving [11]. Apart from some early results, the use of wearable in this domain has so far remained unexplored. We, therefore, ask whether the emerging quantity and diversity of wearable devices along with everyday growing use of smartphones can be exploited to achieve more accurate, intelligent and smart sensing and operation of the personal lightweight electric vehicles like smart-scooters keeping rider safety in mind.

Towards this goal, this paper proposes an android based smartphone application, STEADi, which is used with a smart insole to evaluate the human body balance tests when riding on smart scooters [10]. The system requires the rider to place a smart insole under each foot, while connected using Bluetooth to a smartphone. The data is collected using the android application, then normalized and used with the orientation sensors data of the smartphone to calculate a balancing score. The balancing score will tell the user if he/she is balancing the scooter properly or not [3]. The application also has features to help the rider in detecting potholes and to track his/her path.

2 RELATED WORK

The progress in technology has given rise to new techniques and devices that allow an unbiased evaluation of balance parameters, hence providing researchers with reliable information on a rider’s ability to balance a personal mobility vehicle.

Ultrasonic sensors have been used to measure short step and stride length and the distance between feet [15].Stephen M. Cain, James A. Ashton-Miller, and Noel C. Perkins studied the physics

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978-1-6654-0362-7/21/$31.00 ©2021 IEEE

behind bike balancing. They conducted experiments indoors that utilize training rollers mounted on a force platform (OR6-5-2000, AMTI), an instrumented bicycle [5], and a motion capture system (Optotrak 3020, NDI) to measure the balancing dynamics of bicycle. The experiments showed that the best method to compute the balance of the ride is the interrelation between pressure distribution and center of mass. National Taiwan University [14] developed a system that uses HTC Diamond, a motorcycle-based smartphone as a hardware platform. The smartphone comes with an external GPS and a built-in accelerometer with a sampling rate < 24Hz. The system uses a unsupervised machine learning approach for pothole detection and is divided into two tasks systems. The server-side task uses a smooth-road model and an SVM(support vector machine) whereas the client-side perform feature extraction, filtering, and segmentation.

The smart-scooter company, Spin, recently announced their advanced driver-assistance systems (ADAS) which will be tested in the second half of 2021 in New York City. Spin Insight [13] has two levels, Level 1 & Level 2. Spin Insight Level 2 is the main ADAS system which is powered by Drover AI's computer vision and machine learning platform. In addition to that Spin's scooters will be equipped with a camera,on-board computing power, and sensors to detect sidewalk and bike lane riding collision alerts. The proposed smart-scooter assistance system provides benefits like rider balance check, pothole detection, and path-tracking whereas the Spin Insight provides collision alerts and parking alerts.

3 SYSTEM DESCRIPTION

3.1 Background and Context

The smart-scooters are an up and coming new mobility service adding to the small yet vast category of bike share and car share. With the use of app-based technology and the smart-scooter, the service provides simple yet intelligent ability to rent the scooter for the short-term. The smart-scooters are powered almost exclusively by an electric motor, after an initial push to start the device.

3.2 System Overview

STEADi is an android application used with a Smart Insole system to assess student safety conditions on campus while riding a smart-scooter. Previously, researchers have attempted to use smartphones to measure Gait symmetry, however, STEADi expands upon this use case by incorporating biofeedback training and novel assessment strategies that can be used in the context of smart-scooters and road safety.

The app has three sections in the main window: balancing mode, tracking mode,and potholes detection mode. With the balancing mode, the user will see a screen that turns shades of red based on the error calculated by the balancing algorithm. In the tracking section, the user can see the path, he/she has been traveling while using the scooter and in the potholes detection mode (PotDetect), the user can detect if there is a pothole on the road and the app automatically tag that place where the PotDetect detected the pothole for future reference.

3.2.1 Wearable Gait Lab [7]

Wearable Gait Lab, is a wearable Gait system developed by SAIL lab at CWRU, which uses a force platform with the capability of measuring ground-reaction forces when worn under a person's foot. The main component of WGL that we used in this project is the Smart Insole System. Smart Insole is an important system for realizing "Gait analysis". Up to 96 pressure sensors were uniformly distributed on the pressure sensor array, which ensures a high spatial resolution for plantar pressure measurement. For details of the design method and mechanism of the pressure sensor array, please refer to the former research [6]. Figure 1 (a) shows a circuit board for signal acquisition and data wireless transmission [7].

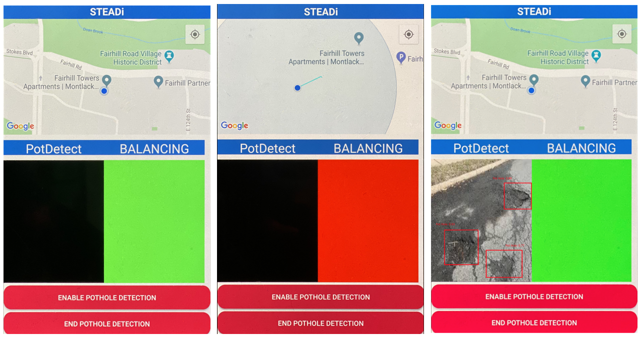
3.2.2 Method to calculate Balance of the rider

The Smart Insole data is recorded, normalized, and used with the orientation sensors data of the android smartphone to calculate a balancing score.

1) A Boolean Cumulative pressure points sum of the 96 pressure sensors was summed, and averaged. $P_Avg_t = \frac{\sum_i^n p_i}{n}$, where n is the number of pressure point sensors and p_i is the recorded pressure for that particular point sensor, P_avg_t is the average total recorded pressure of all the sensors at a time, t.
2) A comparison is made between every 5 seconds, $P_Avg(t-5), P_Avg(t)$ the Boolean Cumulative pressure points sum.
3) If the average pressure has increased or decreased on the insole in the next 5 seconds, a boolean balance variable,"ifbal", is recorded. The "ifbal" is TRUE if the pressure remains the same every 5 seconds and if there is a change in overall pressure the "ifbal" variable is changed to FALSE. If $P_Avg(t-5) > P_Avg(t)$, the average pressure decreased, which means the pressure on the insole is not evenly distributed.

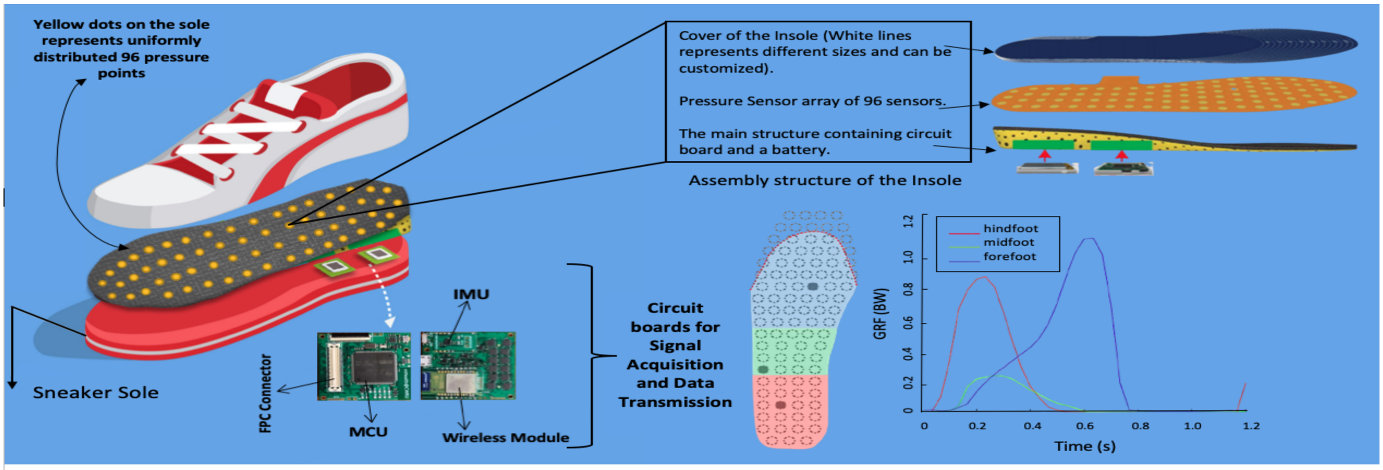
Considering wavy rides or riders doing some tricks, we took roll (the rotation of the smart phone about the positive Z-axis towards the positive X-axis) and azimuth (the angle between the magnetic north and the positive Y-axis and its range is [0,360] degrees) into consideration. The imbalance range of the roll is $[-\infty, -1.0]$ $[1.0, \infty]$ and the range of azimuth is$[-\infty, -0.75]$ $[0.75, \infty]$.

If the "ifbal" variable changes value every 5 seconds and the recorded values of the roll and azimuth are in the imbalance range then we can say that the rider is not balancing properly and the screen section of the "Balancing" will change to RED. Figure 2 shows the screens of the STEADi application, when the rider is balanced and when unbalanced.



(a) (b) (c)

Fig. 2. (a) The STEADi application when the rider is balanced (b) The STEADi application when the rider is not balanced(c) The STEADi application detecting potholes on the road.



(a) (b)

Fig. 1. Hardware and Software of Smart Insole System. (a) 3D bifurcation of the Insole System with Assembly structure (b) Insole Foot Pressure measurement for fore, mid, and hind section. The highest pressure in that area during a stride is indicated by the black dot in each area. The Red dashed line indicates US sized insole used in this research. The Graph shows the measured GRF of each area during a gait cycle.

3.2.3 *Path Tracking*

The path tracking mode allows the user to track its path while riding the Smart-scooters. In this section we use Google Maps API for Android. The API handles access to the Map's server, map display, data downloading, and response to map gestures. The API also provides additional information for map locations and allows user interaction with the map. For more information related to Maps SDK please refer to [9]. For each session, the system automatically prints out the route user has traveled.

3.2.4 *PotHoles Detection*

For this feature, we utilized a previously implemented OpenCV Library on Android for loading a deep neural network model that detects potholes, DefectDetect [1]. The model returns four vertices that outline each pothole; we further decorate the user interface and make it into a more interpretable rectangular box. Structures and some weights of the model we use come from [12] [2]. The working of the pothole detection system in the STEADi application can be seen in Figure 2(c).

To maximize its performance on this specific task, we tweaked the model, and re-trained the final two layers with well-labeled pothole images for 20 epochs. All training images come from a crawler program provided in OpenCV. During the training process, we use mean squared error as a loss function.

$$L(y, y') = \frac{1}{N}\sum_{i=0}^{N}(y - y_i')^2$$

where $L(y, y')$is the mean squared loss and y' is the predicted value.

The detection module will automatically make the phone vibrate if there is any pothole detected by the front camera.

4 EXPERIMENT

4.1 Experiment design

6 riders (3 experienced and 3 inexperienced smart-scooter riders) were asked to perform various experiments. We used SPIN smart-scooters and ride in the below mentioned scenarios.

1) Up and down the slopes: The rider rides the scooter on the road with slopes with the insole in his/her shoes.
2) On the Grass: The rider rides the scooter on the grass/ muddy road conditions with insole in his/her shoes.
3) On the Roads with numerous small potholes: The rider tries to ride on a road with numerous potholes so that we can collect data as to how the pressure changes under this condition.
4) A new rider.

The riders were asked to perform the experiments with the smart insole system and without the insole system. All 6 riders were asked to fill an evaluation form after the experiment. During the experiment, all the gait parameters from the smart insole were recorded using a smartphone. The smart insole pressure values were recorded for each scenario and saved into a CSV(comma separated values) file.

4.2 Experiment Results and Discussion

Mainly two experiments were conducted based on different scenarios mentioned in section 3.1. Based on the data recorded from the insole system, it was seen that the cumulative values of the 96 insole pressure sensors lie within the range of [2,3.2]. When there is very little pressure exerted on the insole the value recorded is 2 and 3.2 is recorded when the pressure exerted on the insole is maximum. If a rider is standing on the ground the pressure recorded was in the range [2,2.5]. But when the rider puts his/her foot down to balance the scooter the pressure exerted was in the range [2.9,3.2]. This is due to the fact that when a person is standing on the ground the surface area is more and pressure is distributed equally between both feet, whereas when a person is trying to balance and puts the foot down, the surface area on which body is trying to balance is that of one foot and hence more pressure is exerted.

4.2.1 *First-time rider of the smart-scooter*

Figure 3 shows the pressure distribution of a first-time rider of the smart-scooter. The graph shows that the rider exerted pressure is unstable. An elevation in the graph indicates that the rider puts his/her foot down because of unbalancing the scooter, whereas whenever the pressure values are dipped that shows the rider is trying to balance the scooter by exerting less pressure. After the 100 ms mark, the rider had some problems balancing and is putting the foot down the scooter more often due to unbalancing the scooter. 2 out of the 3 new riders found that the balancing algorithm was accurately able to evaluate the balancing of the rider, whereas one rider found that the balancing algorithm was about 75% accurate when riding near or around uneven road conditions.

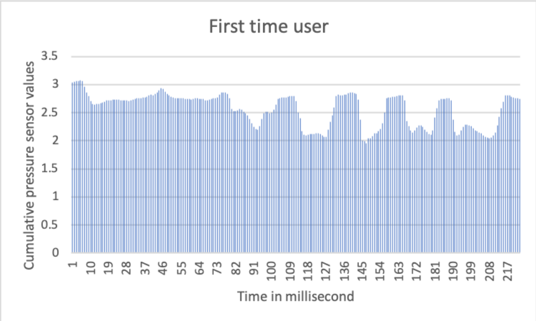


Fig. 3. Insole sensor data when the rider was riding for the first-time.

4.2.2 *Riding scooter on different terrains: Up and down the slope and riding on the grass*

All the 6 riders were evaluated during this experiment. An average rating of $\frac{8.5}{10}$ was given to the balancing algorithm. The max pressure on the insole system can be recorded in two scenarios. First is seen when the user goes up and down the hill and second, when on the grass. The values collected on the grass and the slopes were interestingly the same. The possible reason is that due to not very sturdy ground the body weight pressure on the insole increases. Figure 4 represents when the rider goes up and down the slope. The sudden changes in the pressure values suggest potholes on the road. The potholes can be differentiated by the foot-down action of the rider based on time.

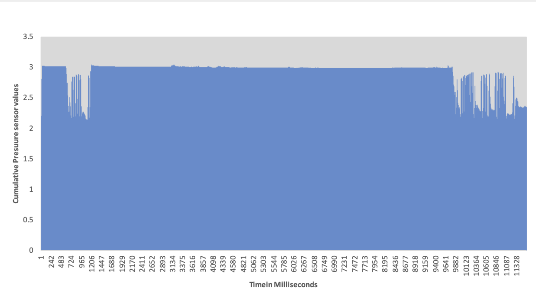


Fig. 4. Insole sensor data when the rider goes up the hill.

4.2.3 *Results and Evaluation of the system*

The pothole detection algorithm was tested in real-time using the android smartphone as well as on a computer on 200 images. The performance metric used for measuring the performance of pothole detection was Recall and Precision. The method obtained scores of 82.56% average precision and 84.12% recall. The system reached the processing speed of 0.031s (31 FPS) as compared to when deployed on a smartphone the processing speed decreased to 0.016s(16 FPS), due to a larger reduction in model size and computation complexity.

5 CONCLUSION

We present an android based smart-scooter rider assistance system which consists of four main modules: mobile application, cameras, Insole sensors, and Google maps API. These modules allow the system to recognize rider or scooter balancing behavior and produce alerts and warnings during dangerous situations like imbalance and potholes are detected. The STEADi app was tried on multiple android devices. It was found that the app glitches on older devices because the OpenCV module is consuming a tremendous amount of resources. We offloaded the UI thread by leaving all computation to other threads and it still did not solve the issue. For some outdated devices, simply updating feedbacks from background threads are difficult to finish in a real-time fashion. The smartphone-based solutions we elaborate here does not require any specific model of scooter, because core sensor is placed inside of shoes and auxiliary sensors are accelerometers and gyroscope that come with mobile devices. [8]

ACKNOWLEDGMENTS

This work was supported in part by the National Science Foundation under Grant NSF-2026612, in part by the UA I-Corps Sites from the National Science Foundation, and in part by the Technology Validation and Start Fund (TVSF) from the Ohio Third Frontier.

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