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ScienceDirect

Procedia Computer Science 224 (2023) 266–273

Procedia Computer Science

www.elsevier.com/locate/procedia

The 20th International Conference on Mobile Systems and Pervasive Computing (MobiSPC)
August 14-16, 2023, Halifax, Nova Scotia, Canada

Towards Human-Centered Pavement Quality Annotation with Crowdsourcing

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Abstract

The maintenance and rehabilitation of road pavements are critical to ensure safe and efficient transportation. To achieve this, accurate and up-to-date information on pavement conditions is necessary. Professional pavement monitoring is a time-consuming and expensive process. In this paper, we focus on the process of identifying and labeling pavement distresses, which we term as "pavement annotation". We explore the potential of engaging drivers and passengers in pavement annotation with crowdsourcing to provide a cost-effective and scalable solution. Our approach involves developing a mobile application prototype that collects both mobile sensor data and human perception data during map navigation. We use an iterative design and development process to create a user-friendly interface that enables the efficient and effective annotation of pavement distresses. We evaluated the reliability of physical model indices computed with the mobile sensor data, the quality of human-labeled road anomalies, and the alignment of the two. Our findings suggest that while challenging, there is a great potential to augment the sensor and human data to generate rich pavement-quality annotation with crowdsourcing. We highlight the advantages and disadvantages of sensor-based and human-driven pavement quality annotation and draw design implications for crowdsourcing software and artifacts to enable safe, scalable, and sustainable pavement annotation.

Keywords: crowdsourcing; pavement quality; human perception

1. Introduction

Road pavements are critical infrastructure that facilitates transportation and plays a vital role in supporting economic activities. However, pavements are subjected to various types of distress due to the impact of traffic loads and weather conditions. To ensure their safety and longevity, accurate and timely monitoring of pavement quality is crucial for developing effective maintenance strategies. Traditional methods of pavement quality monitoring, such as manual

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10.1016/j.procs.2023.09.036

inspections, can be time-consuming, expensive, and prone to human errors. To address these challenges, researchers have explored the use of mobile sensing and crowdsourcing as potential solutions for pavement quality monitoring.

Mobile sensor data, collected using smartphones equipped with GPS and inertial sensors, can be used to estimate pavement roughness and texture. However, the quality of the data collected using smartphone sensors may vary due to the smartphone's position, orientation, and calibration, leading to less reliable estimates of pavement quality indices, such as the International Roughness Index (IRI) [13] and Power Spectral Density (PSD) [1].

Crowdsourcing has emerged as a promising approach to mitigate human errors by aggregating contributions from a large group of people. In contrast to automated sensor data collection, crowdsourcing capitalizes on human insight and contextual understanding, which contribute to the production of high-quality annotations. While crowdsourcing has been applied to collect and aggregate mobile sensor data from multiple devices [11, 5], the engagement of drivers has been considered purely negative and avoided in prior approaches.

This paper evaluates the feasibility of crowdsourcing pavement quality annotation by integrating human perceptions with sensor-based physical-model indices to improve the accuracy and reliability of pavement quality estimates and further enrich the pavement quality assessment with human-centered metrics. To this end, we investigate the key challenges of engaging drivers and passengers in pavement quality annotation and explore the potential of using crowdsourcing to collect and augment both mobile sensor data and human perception of pavement quality. Specifically, this work aims to answer the following research questions: *RQ1. What are the influencing factors for the quality of sensor data collected from mobile devices in some vehicles? RQ2. What are the challenges in crowdsourcing pavement annotations from drivers and passengers? RQ3.Do the roughness measures computed with physical models align with human perceptions?*

We formulate the problem of *Pavement Annotation* as the process of identifying and labeling pavement distresses. To support multi-modal data collection, we developed a mobile application prototype that collects both mobile sensor data and human perception data during map navigation. Using this mobile app, we conducted two feasibility studies on engaging drivers and passengers in pavement annotation. Our result analysis examines the reliability of physical model indices computed with the sensor data collected from different smartphones placed in different vehicles and in different positions (RQ1), the consistency of human-labeled road anomalies (RQ2), as well as the alignment of the two (RQ3). The paper summarizes the advantages and disadvantages of sensor-based and human-centered pavement quality annotation and draws design implications for crowdsourcing software and artifacts to support pavement annotation. By addressing the challenges of traditional pavement quality monitoring methods, this paper provides valuable insights for developing more scalable, sustainable, and human-centered pavement monitoring systems.

2. Related Work

2.1. Current Practices and Challenges in Pavement Quality Monitoring

Road pavement maintenance is critical to ensure safe and efficient transportation [14]. Pavement distresses, such as cracks and potholes, tend to worsen over time due to traffic loads and weather conditions, leading to increased maintenance costs and potential safety hazards for drivers. Prompt repairs can prevent further damage and extend the pavement's lifespan, ultimately saving costs in the long run. In addition, repairing pavement damages early can also improve ride quality, reduce noise, and enhance the overall driving experience. Delaying repairs, on the other hand, can lead to more severe damage, resulting in more expensive repairs or even pavement replacement. Monitoring pavement quality in a timely and scalable manner is therefore essential to prioritize timely maintenance and rehabilitation of pavements to ensure their safety, durability, and longevity.

Pavement quality monitoring is time-consuming and labor-intensive, as it requires trained personnel to travel to different locations, visually inspect the pavement, and record the data with specialized vehicles and equipment. Typically, the quality of pavement is measured by physical models such as International Roughness Index (IRI) [2] and Power Spectral Density (PSD) [7]. IRI is calculated based on the vertical deviations of the pavement surface from a straight line. Higher IRI values indicate a rougher pavement surface, which can lead to increased vehicle wear and discomfort for passengers. PSD is a measure of the distribution of frequencies in a signal or data set. In the context of pavement analysis, PSD is used to quantify the roughness or texture of the pavement surface at different spatial scales.

Collecting the data needed for assessing pavement quality usually requires specialized vehicle-mounted equipment such as profilometers, laser scanners, or cameras. Pavement quality assessments also involve visual inspection by trained technicians or engineers who examine the pavement surface and identify different types of distress such as cracks, potholes, rutting, and other surface irregularities [4]. These processes require specialized equipment such as road distress survey vehicles or handheld devices, and the data collected is then manually analyzed and processed to determine the condition of the pavement.

2.2. Mobile Sensing for Pavement Quality

To address the challenges in professional pavement monitoring, researchers in mobile computing have explored the use of smartphones equipped with GPS and inertial sensors as a potential solution for collecting data on pavement roughness and texture. By using mobile applications to capture acceleration and vibration data while driving on the pavement surface, smartphones can be used to estimate road roughness through the calculation of IRI or PSD at a lower cost and with greater convenience compared to specialized equipment [16, 11, 6]. However, a potential drawback of using smartphone sensors for computing IRI or PSD is that the quality of the data collected may be impacted by factors such as the smartphone's position, orientation, and calibration. Additionally, the accuracy and precision of the sensors on smartphones can vary depending on the device's make and model, as well as the software used to collect and process the data.

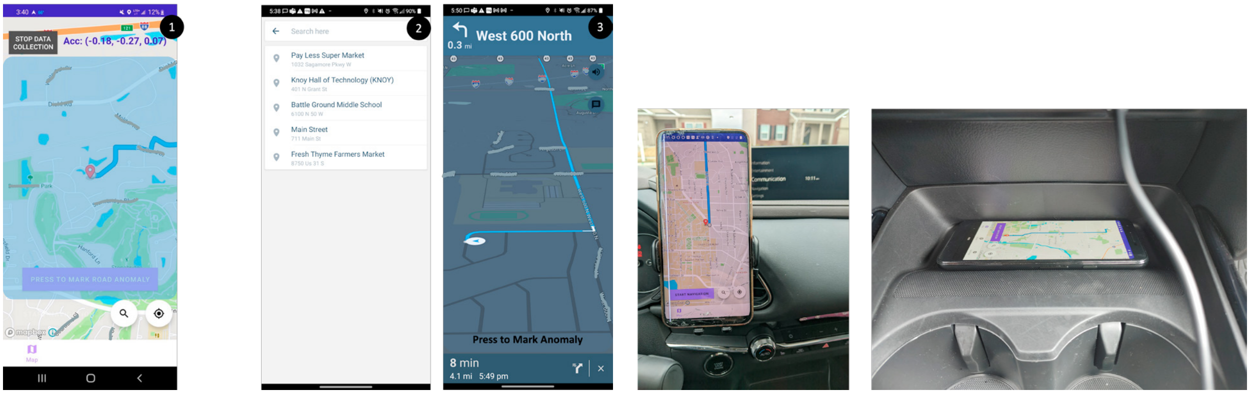
Dong and Li [8] collected accelerometer and GPS data from smartphones that were fixed on the dashboard. They were one of the early people to employ the K-means clustering algorithm to analyze the data and employed PSD analysis for the identification of periodic signals from test vehicles. They filtered out the periodic signals and used inverse FFT to reconstruct the signals. Lee et al [10] proposed an FCN (Fully Convolutional Network) based road-surface anomaly detection with accelerometer-based data acquisition. They used photos clicked from a smartphone camera which is then fed into a simple DNN (Deep Neural Network) to detect anomalies. In addition to acceleration and GPS, Basavaraju et al [3] in their paper also collected gyroscope readings. A DJI Osmo was used to record videos of the road surface to facilitate road condition labeling in the pre-processing stage. Feature extraction was done in 3 domains - time domain features, frequency domain features, and wavelet domain features. After employing SVM, decision tree, and neural network, it was found that machine learning models trained with features extracted from all three coordinate axes give significantly higher accuracy, precision, and recall rates as compared to models trained with features from only the axis perpendicular to the ground.

2.3. Crowdsourcing Annotations on the Road

Professional pavement monitoring methods face the challenge that manual inspection of pavements is often prone to human errors, which can result in inconsistent results depending on the experience and judgment of the inspector. Crowdsourcing is an effective paradigm to augment the wisdom of crowds and mitigate human errors made by individuals [9]. However, it is expensive and unscalable to crowdsource pavement inspections from pavement experts with the high requirement of equipment and expertise. Crowdsourcing with citizen scientists and/or novice people has been applied to the transportation context [12]. Prominent and successful examples include traffic incidents (Waze[1]) and pedestrian accessibility assessment [15]. Yet, different from traffic incidents, identifying and labeling pavement distresses requires continuous inspection and annotation of the road surface, thus unsafe and unsustainable for drivers to participate in such crowdsourcing processes. While Waze has successfully aggregated traffic-related data from a large group of people, the reports related to pavement quality are embedded under "hazard" and the results are not shared in the interface like other information such as "police" or "construction".

Our work builds on and differentiates from prior research in that previous methods have primarily focused on collecting and aggregating mobile sensor data from multiple devices while neglecting the potential benefits of in-situ human annotations for improving pavement quality assessments. We identify design implications for incorporating human annotations through crowdsourcing to overcome the limitation that data collected by smartphone sensors. The

[1] https://www.waze.com/



(a) Pavement Annotation Interface. Picture 1 shows the interface without going into navigation mode. Users can press anywhere in the blue shades (the translucent rectangular box in the middle of the screen) to mark road anomalies. Picture 2 shows the search feature and Picture 3 shows the annotation feature within the navigation mode. Users can press anywhere on the map to mark an anomaly. Road names are masked for anonymity and privacy.

(b) Set-up of Study 2. Two phones were used to collect sensor data for each trip. Through a preliminary survey study on Amazon Mechanical Turk, we collected responses from 300 turkers about where they typically place their phones when driving. The most popular answers were phone mount on the vent and console space. We thus selected these two positions in our study. The human annotations were collected from the phone mounted on the vent.

Fig. 1: The RoadGazor App Interface (a) and Study 2 Set-up (b).

use of human perception and expertise to augment sensor-based indices can also provide richer insights into how road anomalies impact drivers directly.

3. RoadGazer: a Mobile Application for Pavement Annotation

We conducted an iterative design towards a simple and easy-to-use data collection interface. Our pipeline consists of multiple users collecting data via an app and providing it to a central hub for pre-processing and then data analysis.

Annotation Interface. We have developed an Android app called "RoadGazer" that combines pavement annotation and sensor data collection features with a regular navigation app similar to Google Maps or Apple Maps. To enable and encourage large-scale participation in pavement annotation within participants' regular navigation routines, the app provides standard features such as location searching, route mapping, and navigation. Users can mark any pavement anomalies they encounter during their trips.

Sensor Data Collection. The app allows recording data from the built-in accelerometer, gyroscope, and magnetometer during navigation. Data can be collected in both navigation and non-navigation mode. All data are stored locally on the phone in CSV (Comma Separated Values) format. Given the variability in smartphone specifications and performance, we configure a sampling rate of 50 Hz. This rate serves as a hint to the system and does not guarantee a consistent data collection rate of 50 Hz across all smartphones [2]. The actual rate at which events are received can vary, as it is determined by the Android operating system. Consequently, events may be received at a faster or slower pace than the specified rate.

Sensor Data Calibration and Storage. When data is received from the sensors, we convert it to the frame of reference of the Earth in the smartphone before saving it. This ensures that data collected from different smartphones are in the same frame of reference, making it coherent for analysis. The data and attributes we collect from the phone include the timestamp, acceleration with respect to Earth in the x, y, and z directions, latitude, longitude, speed (in m/s), linear acceleration in the x, y, and z directions, acceleration in the x, y, and z directions, magnetometer readings in the x, y, and z directions, and anomaly status (a Boolean value where 1 indicates a road anomaly and vice versa).

[2] https://developer.android.com/reference/android/hardware/SensorManager

4. Study 1: Collecting Sensor Data and Passenger Annotation

In the first study, we employed two vehicles, a compact Sports Utility Vehicle (SUV) and a full-size SUV, each equipped with phone holders for data collection using RoadGazer. Passengers in each vehicle performed pavement annotation using the app while the smartphones were mounted on the holders to ensure consistent data collection throughout the trip. Both vehicles completed two round trips on public roads, totaling four routes, with each route lasting 10-15 minutes. The vehicles were driven one after another to minimize potential confounding factors such as weather, traffic, and pavement status, ensuring a controlled environment for data collection. The smartphones used on the two vehicles were both Google Pixel 5a.

4.1. Data Preprocessing

We generated 4 files from RoadGazer, comprising a total of 101,904 rows and 16 columns. To remove noise resulted from engine vibrations, door movements, phone displacement and other sources, we conducted a four-step data transformation process. Firstly, a high-pass Butterworth filter was applied as the initial transformation, followed by the utilization of the Fast Fourier Transform (FFT) to calculate the frequency components within a time-varying signal. The absolute values of the complex numbers obtained from the FFT were then derived for further analysis. Next, the data attributes were standardized to eliminate disparities in units and ranges and to prevent the Machine Learning (ML) models from assigning disproportionate weight to attributes with higher numeric values. Subsequently, the sliding window technique was implemented, where k data points were combined into a single data point to enhance the accuracy of labeling. To ensure an adequately sized dataset, a window size of k=50 was selected. Overlapping windows with a 50% overlap were employed to address overlapping anomalies, resulting in a dataset comprising 4077 rows and 26 columns. Furthermore, feature engineering was performed by incorporating the standard deviation of 50 attribute values as an additional attribute.

4.2. Data Analysis

We employed both unsupervised and supervised machine learning methods for our anomaly detection task. For unsupervised learning, we used the K-means algorithm to identify k clusters in our dataset. This method involves grouping data points that are relatively closer to each other into one cluster, representing one class.

It merits emphasis that we consciously chose not to deploy deep learning models, which are currently lauded as state-of-the-art solutions in the fields of Computer Vision (CV) and Natural Language Processing (NLP). Our decision was driven by two central factors: Firstly, deep learning models prove particularly beneficial when handling data characterized by intricate interactions and nonlinearities. Nevertheless, these attributes are not directly applicable to our anomaly detection task. Our objective revolves around discerning sturdy correlations between sensor data and human-labeled anomaly data points. Consequently, the elaborate modeling of complex relationships, a forte of deep learning, is not an essential requirement in our scenario. Furthermore, the performance superiority of deep learning models tends to amplify as the volume of the available dataset escalates. In our situation, we are contending with a relatively constrained dataset. Employing deep learning models under these circumstances could potentially induce overfitting, thereby undermining the broad applicability of our conclusions.

One of the main challenges we faced in supervised learning was the highly imbalanced nature of our dataset, with significantly fewer anomaly data points (448) compared to normal data points (3629) after applying the sliding window technique. To address this, we tested penalized versions of our models, which assign higher weights to the class with fewer data points to counteract the imbalance. Additionally, we considered oversampling techniques to increase the number of anomaly data points, although this can sometimes lead to overfitting. In general, oversampling tends to provide better results than undersampling, as the latter can result in a loss of important information. Undersampling of non-anomaly data points was also not practical, given the limited number of data points in the anomaly class.

We compared the performance of several models, including logistic regression, random forest, SVM, and XGBoost, using a stratified 80:20 split of our data into training and testing sets. Ensemble-based models such as random forest and XGBoost were chosen, as they are not affected by the imbalanced distribution of classes in the dataset.

While none of the models performed perfectly, Random Forest outperformed the other models, not surprisingly. To further improve performance, we implemented the Synthetic Minority Oversampling Technique (SMOTE), which

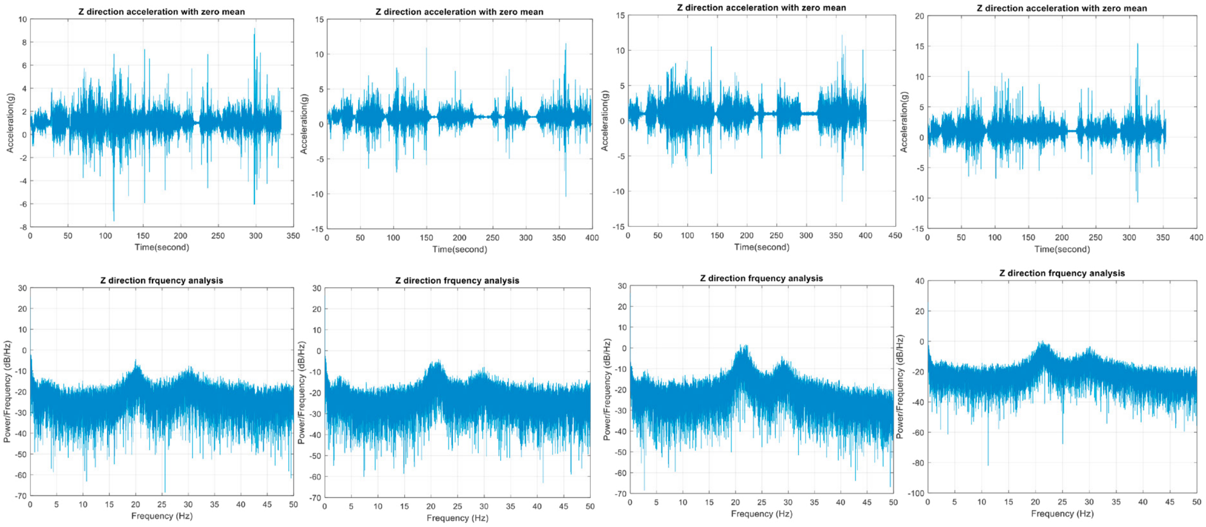


Fig. 2: PSD and Sensor Data Consistency between Multiple Trip Occurrences (an Example).

generates synthetic samples for the minority class. SMOTE overcomes the overfitting problem posed by random oversampling by focusing on the feature space to generate new instances with interpolation between positive instances that lie together. Applying Random Forest after SMOTE led to an improved, albeit not perfect, results.

Table 1: Performance metrics of supervised models

Model	Penalization	Accuracy	Precision	Recall	F1 score	ROC
Random Forest	Non-Penalized	95.78	92.45	22.58	0.363	0.945
	Penalized	95.95	94.82	25.34	0.400	0.949
Logistic Regression	Non-Penalized	94.60	44.44	5.53	0.098	0.832
	Penalized	79.32	16.77	72.81	0.273	0.845
SVM	Non-Penalized	95.14	80.64	11.52	0.202	0.917
	Penalized	91.07	34.96	78.80	0.484	0.919
XGBoost	Non-Penalized	96.73	85.46	46.50	0.600	0.953
	Penalized	96.61	69.67	64.38	0.668	0.952
RF after SMOTE	Only Over	96.56	67.90	67.28	0.676	0.950
	Over and Under	96.81	73.77	62.21	0.675	0.948

The observed high accuracy values for each model may give the impression of robust performance. However, it is important to note that our dataset is highly imbalanced, making accuracy an unreliable metric to evaluate model performance. Instead, we focus on precision and recall, which are low or only high for one of the metrics. This imbalance in precision and recall translates to low F1 scores, which are more appropriate to assess the models' effectiveness. Thus, we aimed to increase the F1-scores by testing various optimization strategies, including different transformations and combinations thereof. In the final row of the table, we achieved our highest F1-score of 0.675 without using FFT and Butterworth filter transformations. We implemented a sliding window technique with 50 windows and 50% overlap to optimize our results.

5. Study 2: Consistency and Alignment of Human Pavement Annotation and Physical Models

In the second study, we collected data from one driver and one vehicle from two repeated routes 20 times. The goal is to understand how consistent an individual user's pavement annotations are on the same route, and how much the roughness index computed with physical models aligns with the human perception.

5.1. Sensor Data Consistency of Different Phones and Trip Occurrences

To measure the similarity of sensor data collected from different phones and occurrences of the same route, we utilized cosine similarity. It is important to note that there were variations in the data collection start and end times, as well as differences in traffic conditions, such as red lights, traffic jams, and unexpected stops, which varied between different trips. To account for these differences, we first aggregated the raw sensor data file by longitude and altitude information. We then augmented the data by interpolating the sensor data for location points within a radius of one meter and adding up the human labels to obtain weighted annotations. Any records with a speed lower than one meter per second are removed from the data aggregation process. The cosine similarity computed from the resulting data demonstrated a high similarity between the two phones placed on the same vehicle (mean=0.96) as well as the same phone among different occurrences of the same trip (mean=0.87).

5.2. Alignment of Human Annotations and Physical Model Calculations

To understand the alignment between human perceptions and physical model measurements, we computed the International roughness index (IRI) of the augmented sensor data and compared it with the corresponding human-labeled route segments. IRI is widely used road index to represent road roughness. According to the Federal Highway Administration in the United States, roads with an International Roughness Index (IRI) measurement below 95 in/mi (1.50 m/km) are generally categorized as being in "good" condition. An IRI ranging from 96 to 170 in/mi (1.51 to 2.68 m/km) is considered "acceptable", while an IRI surpassing 170 in/mi (2.68 m/km) is classified as "poor". [3] We computed IRI values based on the acceleration power spectral density (PSD), which is calculated from time-acceleration data through the vibration test. The power spectral density of the signal describes the power present in the signal as a function of frequency. To measure the alignment between IRI and human labels, we use the Dynamic Time Warping (DTW) algorithm, which is a well-known technique for measuring the similarity between two-time series with different lengths. Since the human annotations were collected through binary ratings, where users log their annotations only when anomalies are perceived, we first examine cases where the pavement quality is classified as either good (IRI below 95 in/mi) or poor (IRI above 170 in/mi). and assess whether the logged anomalies align with the IRI classifications. We used the IRI as the reference time series and the human-labeled segments as the target time series. We then computed the DTW distance between the two series, which is a measure of the dissimilarity between them. A smaller DTW distance indicates a higher alignment between the IRI and human labels.

Our results showed limited alignment between the IRI classifications and the human annotations. To further investigate the underlying reasons, we examined the human annotations and IRI values. We found that the human annotations are quite sparse, and the same road segment received quite different annotations on different trips. Analysis of agreement using Krippendorff's alpha on annotations made during different trips revealed low agreement for annotations pertaining to the same road segment across trips. Through interviews with human annotators, we found that the perception of road quality can vary significantly due to factors such as traffic and weather conditions, and more importantly, the cognitive state of the driver. Two notable factors were identified: (1) the stress level resulting from pressures from their personal or professional life, or being in a hurry, and (2) distractions caused by listening to podcasts or audiobooks while driving. As a result, human annotations are typically made in two scenarios: when severe anomalies are perceived on the road or when the cognitive load from the above-mentioned factors (traffic, stress, distraction from audio playing) is low, enabling the driver to allocate more attention to evaluating the road quality. This hypothesis is further confirmed by the fact that the most labeled anomalies had a strong correlation with the higher IRI values, co-occurring at a few road segments that had severe potholes.

6. Discussion and Conclusion

The findings from our feasibility studies provide valuable insights into the factors influencing the quality of sensor data collected from mobile devices in various vehicle positions (RQ1). We discovered that although factors like smartphone type and mounting position can be addressed through coordinate calibration and noise filtering, capturing and

[3] https://www.fhwa.dot.gov/policyinformation/pubs/hf/pl11028/chapter7.cfm

reducing the impact of road conditions, such as traffic and vehicle types, may present greater challenges. Therefore, we recommend that researchers and practitioners consider traffic conditions and vehicle types when designing mobile data collection protocols to ensure the reliability and accuracy of the collected data. Incorporating human annotation can also help address this variance in the sensor data.

Our study also identified challenges in crowdsourcing pavement annotations from drivers and passengers (RQ2). The criteria for annotations can vary significantly among individuals, and passengers tend to be less perceptive of road anomalies. However, by incorporating a large, easily accessible "button" for marking road anomalies while driving, we effectively reduced cognitive demand and enabled drivers to provide pavement annotations even on public roads. We acknowledge that relying solely on driver annotations is inherently unsafe and unsustainable. Nevertheless, our work suggests that collecting driver annotation data is feasible, particularly when engaging large crowds and/or long-term data collection, as it is highly likely to reveal high-severity pavement defects. Additionally, human annotations can be utilized to train imitation models and predict human perceptions of pavement quality using mobile sensor data.

Lastly, our study examined the alignment between physical model indices and human perceptions of pavement roughness (RQ3). The results indicate a low correlation between physical model indices and human perceptions across most road segments, except when the IRI values are extremely high. This highlights the inadequacy of physical models as reliable proxies for capturing the nuances of human perception, underscoring the importance of incorporating human annotations in pavement quality monitoring systems.

Acknowledgements

Funding for this project was provided by Purdue Polytechnic Holistic Safety and Security (HSS) Research Impact Area Seed Grant, and Purdue Discovery Undergraduate Interdisciplinary Research Internship (DUIRI) program. The findings and opinions expressed in this article are those of the authors only and do not necessarily reflect the views of the sponsors.

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