The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XLIII-B4-2022
XXIV ISPRS Congress (2022 edition), 6–11 June 2022, Nice, France

PROBABILISTIC-BASED CROWDSOURCING TECHNIQUE FOR ROAD SURFACE ANOMALY DETECTION

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Commission IV, WG IV/4

KEY WORDS: Road Surface, Anomaly, Smartphone, Sensor, Crowdsourcing, Web.

ABSTRACT:

Road surface monitoring is a critical key factor to serve the purpose of road safety and driving comfort. Recently, many efforts have been made in developing approaches to detect road surface anomalies using smartphone sensors. However, detecting road surface anomalies from smartphone sensors face considerable number of challenges due to the various factors affecting detection rate. By aggregating data from a large number of users (i.e., concept of crowdsourcing), the accuracy of detection can be increased, and the potential false positive and false negative detection rates raised from every single source (i.e., user) can be detected and filtered. In this paper, a novel probabilistic-based crowdsourcing technique is proposed to classify and combine road surface anomalies (i.e., dynamic events) detected from various smartphones on-board vehicles. The proposed approach can integrate detected events from multiple users which are not an absolute binary scenario primarily caused by different sensing capabilities of various participators' smartphone sensors and diversity in mechanical properties of vehicles. Furthermore, this approach considers the spatiotemporal behaviour of reported road surface anomalies from different users in different times and locations. The experimental results show that the proposed crowdsourcing method improves the accuracy and rate for detecting road surface anomalies.

1. INTRODUCTION

Road surface monitoring is a key task for providing a safe road infrastructure for road users. To this end, road surface condition monitoring aims to detect road surface anomalies such as potholes, cracks, and other surface defects which affect driving comfort and on-road safety. The maintenance and monitoring of road surfaces are challenging tasks for transportation authorities. One of the reasons is that the process requires a substantial volume of reliable and timely data that is necessary for any continuous maintenance and monitoring scheme. Currently, smartphone-based sensing is becoming one of effective approaches since the mobile devices are equipped with a variety of miniature sensors such as cameras, LIDAR, accelerometers, gyroscopes, and GPS. Using smartphones to detect road surface anomalies offers the potential to change the way the government agencies monitor and prioritize road rehabilitation and maintenance and has attracted researchers around the world to explore its solutions.

Advances in sensing technologies and big-data computing of smartphones data, make them attractive for many applications such as monitoring traffic flow, human mobility, and clinical research (Talari et al., 2017). Data aggregation is a critical feature, which should be considered to make these applications more practical and pervasive. However, aggregating data from various smartphones is challenging due to the diverse precision of smartphone sensors (Ouyang et al., 2016). Moreover, recent studies discovered that the GPS accuracy of smartphones is considerably lower than that of a dedicated GPS device designed solely for positioning and navigation purposes. Therefore, integrating data obtained from different smartphones are challenging due to their uncertainty and variability.

Many studies have attempted to use smartphone sensors mounted on a moving vehicle to collect and process data to monitor and locate roadway surface defects (Sattar et al, 2021), (Yi et al., 2015), (Douangphachanh et al., 2014) and (Mednis et al., 2011). However, existing studies are limited to identifying roadway anomalies mainly from a single source and do not exploit the benefits of combined and integrated multi-sensor systems in terms of their accuracy and functionality. By aggregating data from a large number of users (i.e., concept of crowdsourcing), the accuracy of detection can be increased, and the potential false positive and false negative detection rates raised from every single source (i.e., user) can be detected and filtered.

A road surface anomaly detection app for smartphones was developed by Sattar et al. (2021) on Android operating system, to monitors linear accelerometer and gyroscope sensors' data to detect anomalies when a moving vehicle passes through any road surface anomalies. The detected anomalies can be stored locally on smartphones or streamed to a remote storage. However, due to different sensor properties and mechanical properties of vehicles, the detection rates of different smartphones by using the app can vary (Sattar et al., 2021).

To address this problem, the objective of this paper is to develop a probabilistic-based crowdsourcing technique that combines road surface anomalies (i.e., dynamic events) detected from many individual smartphones on-board vehicles, which provide better spatial coverage and continuous observations. This approach further considers the spatiotemporal behaviour of detected road surface anomalies in different times and locations.

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2. METHOD

Figure 1 illustrates the overall process of the proposed crowdsourcing approach.

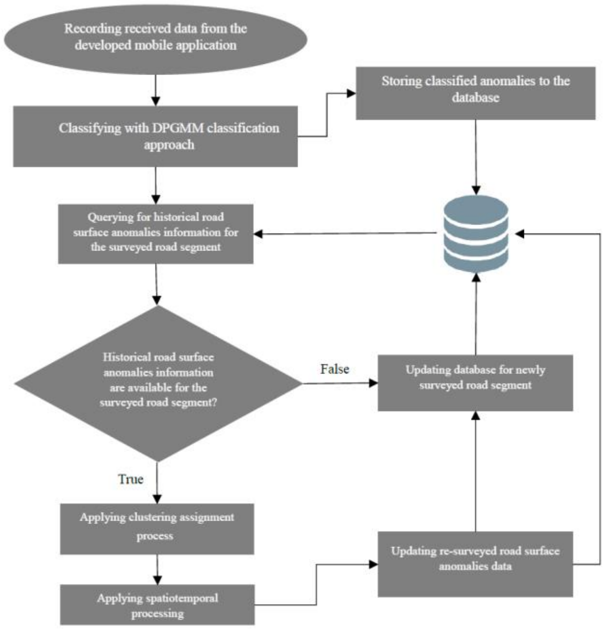

Figure 1. The proposed spatiotemporal crowdsourcing procedure

To collect road surface anomalies of each road segments, the Android-based smartphone app proposed by Sattar et al. (2021) is installed on smartphones on-board vehicles. This app uses smartphone's linear accelerometer sensor to detect road surface anomalies. The app stores detected road surface anomalies, which are the outcomes of the k-means approach for each segment separately, in a Comma-Separated Values (CSV) file format on the local storage of the smartphone. For each detected road surface anomaly, the stored information includes location (i.e., longitude and latitude), the speed at the time of detection, bearing value of moving direction at the time of detection, ratio of the standard deviations (i.e., standard deviation of the event period to the standard deviation of the normal road condition), ratio of the linear accelerometer values (i.e., linear acceleration value in the time of event period to the average value of the normal road condition period), and time of detection. These values are described in detail in Sattar et al. (2021). The stored CSV files are sent to a local computer or server for further processing.

According to Figure 1, the spatiotemporal classification approach consists of the following major steps.

2.1 Classification of road surface anomalies

To classify the detected road surface anomalies from the app, the Dirichlet Process Gaussian Mixture Model (DPGMM) (Christopher, 2016), which is an unsupervised nonparametric Bayesian clustering model, is utilized to classify detected road surface anomalies. The detected road surface anomalies are the outcomes of the developed mobile app.

In fact, the adopted DPGMM classify data events (i.e., detected road surface anomalies from mobile app) to infinite Gaussian mixture models. This model adopts the concept of Dirichlet Process (DP) and Chinese Restaurant Process Mixture (CRPM) to partition the data. The Gaussian mixture model with K components can be derived from the Eq. (1).

$$P(x|\theta_1 + \theta_2 + ... + \theta_n) = \sum_{i=1}^{K} \pi_i \, N(x|\mu_i, S_i) \qquad (1)$$

where $\theta_i = \{\mu_i, S_i, \pi_i\}$ is the set of parameters for component i, π are the mixing proportions (Subject to: $\sum_{i=1}^{k} \pi_i = 1, \pi_i > 0$), μ_i is the mean vector for component i, and S_i is its precision matrix (i.e., inverse of covariance matrix). The DPGMM approach aims to classify road surface anomalies according to the severity level of each anomaly sensed by vehicles.

An archive JSON file format is created to store the information about classified road surface anomalies and formed clusters, required for the cluster assignment and spatiotemporal data processing steps.

2.2 Clustering assignment processing

Once newly detected road surface anomalies are classified (i.e., the outcomes from the Section 2.1), the archive formed clusters which stored in the archive JSON file should be queried to discover any possible formed cluster from prior road surveys to combine them with possible historical information. If any formed cluster is discovered, the new classified road surface anomaly is assigned to the associated cluster based on the following proposed assignment approach. To assign new classified data events (i.e., road surface anomalies) to any possible formed clusters which are stored in the archive JSON file, the geographic location information of the new classified data events and the formed clusters are utilized to find any potential geographic intersection. Due to the uncertainty of the detected geographic location, two steps of geo-query are conducted to find the possible related clusters to which a new classified event can be assigned:

1. Absolute accuracy value reported by Android API for each detected anomaly's geographic location is used to create a buffer area and discover the formed clusters intersected with buffer area.
2. Bearing value of moving direction for each classified data event is used to filter out the intersected clusters from the previous stage which had dissimilar moving directions.

Conversely, if no formed cluster is found in the archive JSON file, the new classified road surface anomaly is stored in the file as a newly detected road surface anomaly which formed a new cluster and store in the archive JSON file.

2.3 Spatiotemporal data processing

This step aims to consider spatiotemporal behaviour of road surface anomalies (i.e., data events) for data integration when newly detected road surface anomalies assigned to any formed cluster from the Section 2.2. Time series road surface anomaly data detected by different smartphones on-board vehicles or surveys at different time should be integrated to infer the most probable and updated information for each road surface anomaly existing on the road surface. To consider all concerns to integrate detected road surface anomalies from multiple road surveys, a spatiotemporal Dirichlet process is developed. This approach consists of several steps. First, the spatiotemporal weight of each anomaly grouped within a cluster is determined using a Gaussian Radial Basis kernel function (RBF). RBF calculates both the spatial and temporal distance from the centroid of that cluster and all observations within the cluster. RBF is one of the widely used kernel function of Gaussian Processing (GP), which is continuous and flexible enough to be positive or negative in various region of space (Rasmussen, 2004). Equation (2) describes the formulation of RBF kernel function:

$$\mathrm{k}(\mathrm{l},\mathrm{l}') = \exp\left(\frac{-\|\mathrm{l}-\mathrm{l}'\|^2}{2\sigma_\mathrm{l}^2}\right) = \exp(-\gamma\|\mathrm{l}-\mathrm{l}'\|^2) \qquad (2)$$

According to the Equation 2, $\|\mathrm{l}-\mathrm{l}'\|$calculates the Euclidean distance of both time and location for each anomaly within a cluster from the current time and the centroid geographic location of the cluster. "l" denotes the array containing geographic location and the time stamp values of each detected anomaly within a cluster. "l′" denotes the array containing the centroid geographic location of each cluster and the latest time recorded for the detected anomaly grouped within a cluster. In this study, $\frac{1}{2\sigma_\mathrm{l}^2} = \gamma$ which defines the width of the bell-shaped curve is calculated based on the standard deviation of the computed time and geographic location distances of each cluster's member.

The outcome array of the RBF process is considered as the weight values (for both time and location) for each detected anomaly. In fact, the closest event to the centroid location of the cluster and the latest detected anomaly, which have both lower distance values have higher weight values. To combine both spatial and temporal weight values of an anomaly to determine the spatiotemporal weigh factor, the weigh values of time and location computed from Equation 2 should be summed. Then, to normalize all computed weight factors to range between 0 value and 1 value and sum to 1, the calculated spatiotemporal weight factors are normalized by dividing each weight factor to the sum of all weight factors. These normalized weight factors are multiplied to each corresponded anomaly's probability distribution to form a weighted-probability matrix.

Then, to estimate the probability distribution of each cluster from the composed frequency weighted-probability matrix, a Dirichlet multinomial mixture (DMM) model, which is a family of discrete multivariate probability distribution, is applied. The Dirichlet-multinomial distribution is a compound distribution where probability vector is drawn from a Dirichlet distribution and then a sample of discrete outcomes is drawn from a multinomial with probability vector. To fit DMM to the composed frequency matrix, the approach proposed by Minka (2000) is adopted and applied.

In addition, to infer the post probable value for the geographic location and bearing value of moving direction in which the anomalies within a cluster are detected, the values of the geographic location and the bearing values of the clustered anomalies are averaged.

3. RESULTS AND ANALYSIS

The results from the proposed approach verified the advantage of the proposed crowdsourcing method to increase the accuracy and reliability of detection rate all dynamic features such as road surface anomalies.

To implement the experiment, a study area was selected in the North York region, in City of Toronto, Canada. The study area (see Figure 2) is composed of four different road segments with different grades of surface roughness. The process of data collection was repeated in five different days between March 21, 2018, and March 30, 2018, to simulate the data collection model operated by different users.

Figure 2. Location for the study area

The app mentioned above was utilized to collect road surface anomalies on the determined road segments. Figure 3 illustrates the main interface of the developed mobile application, in which base map tiles are provided by the Google Maps API. An on-click GUI (Graphical User Interface) button was implemented to manage the start/stop service request from users ("CLICK TO START DETECTION" and "CLICK TO STOP DETECTION"). By clicking on the "CLICK TO START DETECTION" button, the developed detection service starts the processing in the background. And, in the meantime, the GUI button automatically changes to "CLICK TO STOP DETECTION" to manage the requests for stopping the service whenever the user needs to stop the process.

Figure 3. The main interface of the developed Mobile GIS application and its functionalities

To illustrate the detected road surface anomalies in temporal domain, ArcScene, which is a software package provided by ESRI, was utilized. The detected road surface anomalies were represented in a way that the vertical dimension of each detected road surface anomaly demonstrates the time of detection. For example, the red data points, which are in the lower elevation than the other data points, was collected on March 21, 2018, and purple data point, which were in higher elevation, was collected in the last survey conducted on March 30, 2018 (refer to Figure 4).

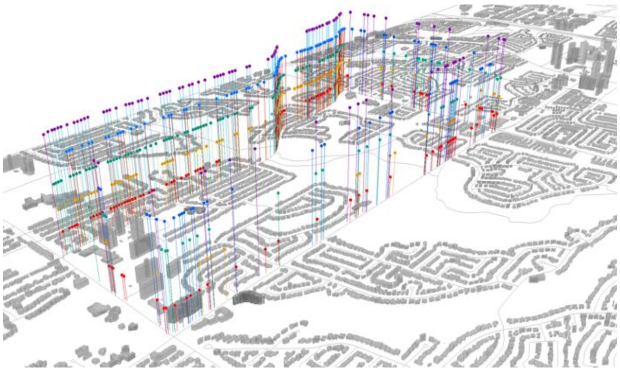

Figure 4. Spatiotemporal representation of detected road surface anomalies

Table 1 summarizes the numbers of detected road surface anomalies for each road segment and for each time of survey. According to Table 1, Cummer Avenue and Finch Avenue both have approximately the same lengths. However, the average number of anomalies detected in Cummer Avenue was about 3.5 times more than anomalies detected in Finch Avenue. On the other hand, Bayview Avenue and Leslie Street are approximately the same length. However, the number of detected anomalies along Bayview Avenue was less than one third of the detected anomalies along Leslie Street. Even though the rate of detections varied in each survey, the pattern of detection was similar between all surveys. By combining and integrating these anomalies detected at multiple times, not only the accuracy of detections increases but also the implication of anomalies' probability distribution is enhanced.

Date	Street Name			
	Cummer Ave	Leslie St	Finch Ave	Bayview Ave
March 21, 2018	86	13	26	6
March 23, 2018	72	14	19	6
March 24, 2018	87	9	20	7
March 28, 2018	72	13	27	4
March 30, 2018	77	10	18	6

Table 1. Total number of detected road surface anomalies for each road segment in each time of survey

Table 2 summarizes the number of clusters for each road segment after applying the DPGMM approach on collected road surface anomalies for each time of road surface anomaly data collection. It was evident that the DPGMM is effective to manage the dissimilarities of available road surface anomalies existing on every road segment and classify them to the most conceivable classes. For example, the detected road surface anomalies on Cummer Avenue, which had the most defective road surface conditions among all the other studied road segments, were classified into either three or four classes. However, the detected road surface anomalies on Bayview Avenue, which had the greatest road surface condition among all those studied road segments, were classified into mostly one or two classes. The outcomes from the DPGMM classification approach specifies that the number of formed clusters was highly correlated with the quality of the roads surface.

Date	Street Name			
	Cummer Ave	Leslie St	Finch Ave	Bayview Ave
March 21, 2018	3	1	2	2
March 23, 2018	3	3	2	1
March 24, 2018	3	1	3	2
March 28, 2018	4	3	3	1
March 30, 2018	3	2	2	3

Table 2. Numbers of formed clusters for each road segment

Then, classified road surface anomalies at different times of survey were clustered together based on the detected location. To perform the clustering process, the classified road surface anomalies from the previous step were passed to this process in the sequence. That is, first, collected road surface anomalies of March 21, 2018, was passed to this process, then collected anomalies data of March 23, 2018, passed for integration. This process continues until passing the last collected anomalies occurred on March 30, 2018. This process aimed to group the multiple detections of every road surface anomaly. Figure 5 illustrates the formed clusters related to the two existing road surface anomalies and all assigned detections to each cluster along Cummer Avenue. Blue and yellow points illustrate the assigned detected road surface anomalies, which were grouped as the potential related detection to these two cluster after five surveys. Red points represent the centroid location of these clusters.

Figure 5. Two clusters with their members

Table 3 represents the integrated probability distribution results for the four different selected clusters. These clusters are numbered as "1", "2", "3", and "4" as depicted in Figure 6. Figure 6 shows the captured images of those selected road surface anomalies recorded during the filed inspections. According to Table 3, Cluster 1 was in Cummer Avenue and has higher likelihood of being in Class 3. Cluster 2 was in Leslie Street and has higher likelihood of being in Class 1. Cluster 3 was in Finch Avenue and has higher likelihood of being in Class 2. The last cluster was in Bayview Avenue and has more likelihood of being in Class 1. However, in all four selected clusters, there was the possibility of such anomalies belonging to other classes in all selected clusters.

Cluster #	Class#1	Class#2	Class#3	Class#4
1	0.00	0.00	0.76	0.24
2	0.53	0.25	0.22	0
3	0.35	0.47	0.18	0
4	0.96	0.03	0.01	0

Table 3. Probability distribution of four selected clusters illustrating four individual road surface anomalies in four different rod segments

Figure 6. Captured photos from studied road surface anomalies

The spatiotemporal data processing step was focussed on integrating the multiple probability distributions of multi-time detections of any road surface anomaly. They were grouped as a cluster resulting from the cluster assigning process to update the level of the severity probability distribution for a detected anomaly as more evidence becomes available. Figure 7 represents the 3D view of the results by integrating road surface anomalies according to their classes which have high probability.

According to Figure 7, the height of each anomaly indicates the severity level of the anomaly (with high probability), which were sensed and integrated after five repetitions of the road surveys. The anomalies which were clustered in Class 1 (first level of severity) with higher probability specifies the least level of severity which were mainly caused by small cracks, even manhole covers, or road joints. However, the anomalies, which were clustered in other classes (i.e., Class 1, Class 2 and Class 3) with higher probabilities, resulted from potholes, big cracks, or uneven manhole covers and should be inspected for further verification.

Figure 7. Outcomes of the spatiotemporal processing of the formed cluster

To assess and verify the accuracy of detection from the proposed spatiotemporal crowdsourcing technique, field inspection was employed to define the number of existing road surface anomalies for every studied road segments. To ensure the accuracy of detection in terms of the detected location and the numbers of detections, in each studied road segment, the detected road surface anomalies from the spatiotemporal processing of each road segment were split into the smaller segments based on the intersection of that road segment with other roads. For example, parts of Cummer Avenue, Leslie Avenue, Finch Avenue, and Bayview Avenue were selected for this study were composed of twelve, eight, six, and three smaller segments, respectively. Moreover, during the field inspection, the number of existing road surface anomalies were counted recorded within those each segment.

The results and the accuracy of detection analysis indicated that the proposed approach in this research were highly capable of merging multiple detections and inferring robust interpretation of each road surface anomalies. Moreover, the accuracy of detection analysis indicated that the drastic improvement of road anomaly detection could be achieved after few rounds of surveys with an overall accuracy of almost 100%.

In Table 4, it is evident that the detection rate drastically improves by using the proposed crowdsourcing approach. In Cummer Avenue, the first round of survey was able to detect the road anomaly with overall accuracy barely over 65%. With one additional survey, the accuracy improved to 77%. The overall accuracy yielded better than 90% all the time after the Cummer Avenue was being surveyed for more than three times. Similar phenomena occur in the Finch Avenue and Leslie Street. The first survey was able to detect the anomaly features with accuracy over 68% and 62%, respectively. While the second and the third surveys improved the detection over 80% and 90% in the respective two roads, additional surveys afterwards improved the accuracy to almost 100%. In Bayview Street, since the road has been recently rehabilitated, fewer road anomaly features exist along the road. As a result, a drastic improvement of road anomaly detection can be achieved after three rounds of survey with overall accuracy improving from 67% to almost 100%.

https://doi.org/10.5194/isprs-archives-XLIII-B4-2022-281-2022

	No. of Survey				
Street Name	**1**	**2**	**3**	**4**	**5**
Cummer Avenue	65%	77%	92%	97%	99%
Leslie Street	62%	90%	90%	100%	100%
Finch Avenue	68%	82%	84%	100%	100%
Bayview Avenue	67%	67%	100%	100%	100%

Table 4. Accuracy detection rate after every data accumulation and processing.

4. DISCUSSION

Road surface anomaly detection from smartphone sensors face critical challenges due to the variability of detection rate, accuracy of detected location, and measuring the intensity anomaly form device to device and from vehicle to vehicle. Also, road surface anomalies have varying properties and they may change from time to time. These uncertainties and variabilities existed in both detection and nature of road surface anomalies led to the use of a crowdsourcing technique to integrate detected road surface anomalies from various users and to combine them to infer more robust and accurate detection information from multiple users. Previous studies investigating the use of crowdsourcing techniques to aggregate road surface anomalies from multiple detections were only in a very early stage and not efficient for implementing in an on-line mode but also suffered from dealing with the uncertainty and variability aspects of road surface anomalies. The research presented in this study provides a probabilistic crowdsourcing approach to aggregate various detections of road surface anomalies from different users in the spatiotemporal domain.

The participatory web-based GIS prototype can be beneficial to both authorities such as ministry of transportation or municipalities to actively monitor, improve and maintain road surface conditions with a low cost by using road user supplied data. In the City of Toronto, citizens can report potholes by completing an online form, calling 311 (the service line of the City of Toronto), or sending emails to authorities reporting the exact location of identified potholes. However, these reporting methods require considerable human interactions and may lead to faulty reports, which are costly for communities.

Based on the proposed crowdsourcing approach, a Web-based GIS prototype could be developed using the Web technology. This Web-based GIS prototype consists of web maps and a client-server architecture to collect, process, store, and continuously display the road surface anomalies detected from multiple users. In addition, this Web-based prototype should be able to query and display anomalies based on the selected time range. Moreover, an event-driven GIS could be developed performing as a sense and respond GIS system, for subscribe/publish notification. The subscriber can be any road user such as drivers or road authorities who are responsible for road monitoring and maintenance including ministries of transportation or municipalities. The system should also notify road users (e.g., sending pop-up messages) through the developed smartphone application and notify them before approaching any road surface anomaly, or inform the road authorities about the high potential of road hazardous areas within the road network.

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