Mining Distributed Collective Intelligence for Accessible Urban Mobility

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***Abstract*—Urban spaces have traditionally been designed with a strong emphasis on motor vehicle traffic, often neglecting the accessibility needs of people with mobility impairments. This approach limits their ability to move independently, interact with their surroundings, and fully participate in urban life. One of the main barriers is not just the physical infrastructure, but also the lack of detailed and accessible information on paths, obstacles, and terrain conditions. Although mainstream navigation tools offer basic pedestrian routing, they typically overlook the specific needs of individuals using wheelchairs or facing similar challenges. This paper investigates how distributed collective intelligence, derived from the aggregation of data and knowledge across urban environments, can be leveraged to support inclusive wayfinding solutions. In particular, we discuss an architecture and two representative mobile applications that demonstrate how mining these collective insights can effectively improve accessibility and contribute to a higher quality of life for mobility-impaired individuals in urban contexts.**

***Index Terms*—crowdsensing, distributed collective intelligence, road accessibility, urban mobility**

I. Introduction

Modern cities are increasingly saturated with vehicle traffic, often used even for short-distance travel. This ongoing transformation of urban spaces has significantly affected quality of life, particularly for individuals facing mobility challenges. The growing gap between those who can move freely and those with physical impairments calls for more inclusive mobility solutions [1].

When navigating unfamiliar areas, most people rely on digital maps that provide directions between locations. These tools are generally effective for the average pedestrian or commuter, but often overlook the accessibility requirements of people with limited mobility. There is a larger need for route planning that considers personalized preferences such as obstacle avoidance, surface quality, noise levels, shaded paths, pollution levels, surrounding beauty, or opportunities to socialize along the way [2]. A key obstacle to building accessible navigation services lies in the absence of granular and inclusive urban data. For example, enabling the identification of routes that avoid stairs or prioritize ramps would require detailed infrastructure data that is rarely available in current map systems. Manually collecting and maintaining such a dataset would involve substantial time and cost.

Partial financial support for this work is provided by the Department of Mathematics of the University of Padua.

Smartphone ubiquity enables a participatory model where citizens use integrated sensors to gather geo-referenced accessibility data. This scalable approach enriches urban maps with vital information for those using mobility aids, fostering greater independence and safety in urban navigation [3].

This concept underpins the system we discuss here, which demonstrates how mobile crowdsensing can mine distributed collective intelligence and support accessible wayfinding [4]. Our solution leverages on decentralized data collection using existing smartphone sensors. The data collected are subsequently processed by back-end services to generate mobility-friendly routes. Beyond the general architecture, we present two proof-of-concept (PoC) implementations designed to identify routes that could be accessible for people with mobility impairments. Then, this information is used to generate routes upon request that prioritize accessibility features such as smooth road conditions, ramps, and low-gradient paths.

The remainder of this paper is structured as follows. Section II provides an overview of the related literature. Section III presents the proposed architecture and discusses the challenges encountered during its design. Sections IV and V then describe two PoC implementations that focus on detecting route conditions. The web and mobile services that generate accessible routes based on collected data are discussed in Section VI. Finally, we draw our conclusion and present some future research directions in Section VII.

II. Related Work

A. Solutions for Accessible Urban Mobility

During the past decade, researchers have developed numerous smartphone applications that leverage sensor data to monitor and classify human activities [5]. These solutions have proven effective in recognizing various user states relevant to urban mobility, such as vehicular transportation, pedestrian movement, stairs navigation, and fall detection. Interestingly, the same technology can be repurposed to identify accessibility features in urban environments such as curb cuts and barrier-free pathways [6], [7]. For instance, accelerometer data from mobile devices can be analyzed to detect road crossing behaviors and infer the presence of pedestrian signals [8]. When combined with collaborative sensing, these approaches can significantly improve both the precision and coverage of accessibility mapping [9].

Several mobile applications have been developed to support wheelchair users. One common approach to these solutions is to rely on community-driven data collection, where users actively contribute to reporting and document accessibility barriers [10]. This user-generated content is often complemented by formal accessibility assessments conducted by trained experts, which is particularly valuable for indoor environments where automated detection fails.

Beyond smartphone-only solutions, several systems integrate the IoT infrastructure, wearable devices, and augmented reality. Indoor navigation systems, for example, use Bluetooth Low Energy (BLE) beacons to guide users through complex buildings while avoiding obstacles such as stairs [11]. For outdoor navigation, context-aware systems provide haptic or audio feedback to help users explore unfamiliar areas. Such systems have been tested on different scales, demonstrating their adaptability to diverse urban environments. Their applications span from controlled, small-scale settings, such as university campuses, to large, complex urban areas [12].

Some projects adopt a hybrid approach that combines automated sensing with human expertise. These hybrid systems generate annotated maps that highlight both accessibility barriers and facilitating infrastructure throughout a city [13].

Finally, mPASS offers a more comprehensive approach by providing personalized route recommendations based on user-specific needs and preferences [14]. Rather than focusing solely on physical accessibility, it considers multiple factors, including safety concerns and whether a route accommodates strollers [15].

B. Detecting Road Anomalies

Three main methodologies have been identified for the detection of road anomalies, namely three-dimensional reconstruction, vision-based analysis, and vibration-based analysis, each of which operates within the supervised learning framework and relies on labeled data to achieve accurate identification and classification of surface irregularities [16].

Three-dimensional (3D) reconstruction entails the generation of precise digital representations of road surfaces through technologies such as the integration of multiple two-dimensional images or the utilization of laser pulse measurements. Instead, vision-based analysis employs cameras installed in vehicles to collect visual data on road surfaces in the form of images or video recordings, which are subsequently analyzed by image processing algorithms [17]. In contrast, vibration-based analysis concentrates on detecting vehicle-induced vibrations resulting from surface irregularities, commonly employing sensors such as accelerometers or gyroscopes. The fundamental premise underlying this approach is that a vehicle is likely to experience increased vibration when traversing an uneven surface compared to a smooth one [18]. Our approach falls into the latter methodology. We hence further explore related work in this realm that generally includes processing data through threshold-based approaches and machine learning [8].

The threshold-based approach identifies anomalies on the road surface using predetermined threshold values established through empirical analysis of sensor data [18]. For example, Li *et al.* [19] employed a smartphone-based accelerometer to monitor variations along the Z-axis, incorporating low-frequency and speed filtering techniques. Another system, known as *TrafficSense* [20], identifies potholes, bumps, and braking events through the use of two speed-dependent detection mechanisms.

III. From Distributed Collective Intelligence to Accessible Wayfinding

In this work, we discuss how distributed collective intelligence can be mined through smartphone-based sensing to support a routing system designed to address the needs of people with mobility impairments. Our approach is based on two key properties: first, modern smartphones already integrate the necessary sensors to detect relevant urban features; second, these devices are widespread enough to enable large-scale passive or participatory data collection without requiring dedicated infrastructure. This kind of large-scale participatory sensing approach is also known as crowdsensing, defined as the collection of sensor and contextual data through the voluntary or opportunistic participation of a distributed community of users. Beyond the general architecture, our solution includes two mobile sensing applications as PoCs, detecting road accessibility: one of them identifies frequently traveled and hence likely accessible routes (Section IV), while the other assesses surface quality and slope conditions to infer route accessibility (Section V). The information collected is then processed to generate accessible wayfinding that can be included in existing digital map navigation services.

We have also created a mapping-based service that leverages on the data collected to provide information on accessibility conditions and routes to users (Section VI). The interaction with the system is done through a customizable routing interface. Rather than presenting a single optimal route, our system allows users to specify their priorities through weighted preferences across different accessibility criteria. The final output is therefore a ranked set of route alternatives, each annotated with relevant characteristics, enabling informed decision-making based on individual needs and circumstances.

A. Design Issues

Developing a system that extracts and elaborates distributed collective intelligence through crowdsensing to generate accessible wayfinding services involves several design challenges that must be addressed to ensure data reliability and sustainable user participation.

Energy consumption and device resources: A key concern is the impact on mobile devices. Continuous monitoring requires sensors to stay active for long periods, which can quickly drain battery life and discourage users. Processing and transmitting large amounts of data, especially in real time, also requires significant resources. To mitigate this, crowdsensing systems often rely on intermittent data collection and delayed transmissions. In our approach, data are uploaded only periodically (when Wi-Fi is available, in the evening, or after user confirmation).

Data heterogeneity and quality: Crowdsensing relies on heterogeneous devices, sensors, operating systems, and sampling rates, producing non-uniform data in accuracy or completeness. Environmental factors and user behavior can further distort measurements. Pre-processing steps such as filtering, normalization, and error correction are therefore essential to ensure reliable data before server-side aggregation.

Privacy and trust: Sensor data may reveal sensitive details about users and must be carefully protected. Privacy can be ensured through anonymization, secure transmission, and transparent data policies, which help build user trust and encourage participation.

User incentives and participation: Crowdsensing requires consistent participation, which is unlikely without clear user benefits. Beyond indirect advantages such as improved accessibility, direct incentives like points, discounts, or recognition can motivate users and sustain engagement.

Scalability and system robustness: As participation grows, data volume increases significantly, requiring scalable storage, efficient processing, and fast data retrieval. The system must also remain robust, managing missing or noisy data and adapting to changes in user behavior or new sensing methods.

B. General Architecture

To address the challenges previously outlined, we designed a modular and layered architecture to mine distributed collective intelligence regarding urban accessibility to generate inclusive routes. Essentially, the entire system architecture and application logic need to be specifically designed considering the target objectives working in a way that guaranties user privacy [21]. This is done by breaking down the overall problem into smaller components that can be addressed individually by dedicated modules of the architecture [22]. As illustrated in Figure 1, the architecture follows a layered approach. At its foundation lies the sensing crowd, which consists of heterogeneous users equipped with mobile devices and embedded sensors. These devices directly collect raw data from the external environment, including ambient noises, lighting, and structural obstacles or accessibility features. Unlike traditional single-device sensing applications, crowdsensing leverages the collective contribution of many individuals, thereby producing a richer and more representative dataset.

In the proposed model, the raw data gathered by the sensing crowd undergoes a preprocessing stage directly on the mobile devices. This step is essential because different devices may generate heterogeneous data in terms of format, quality, or sampling frequency. Preprocessing harmonizes these inputs, filters noise, and reduces redundancy prior to transmission. Importantly, data transmission is not continuous: instead, it occurs periodically, for example, once the device is connected to a Wi-Fi network or after explicit user confirmation or manual correction of collected samples. This approach reduces

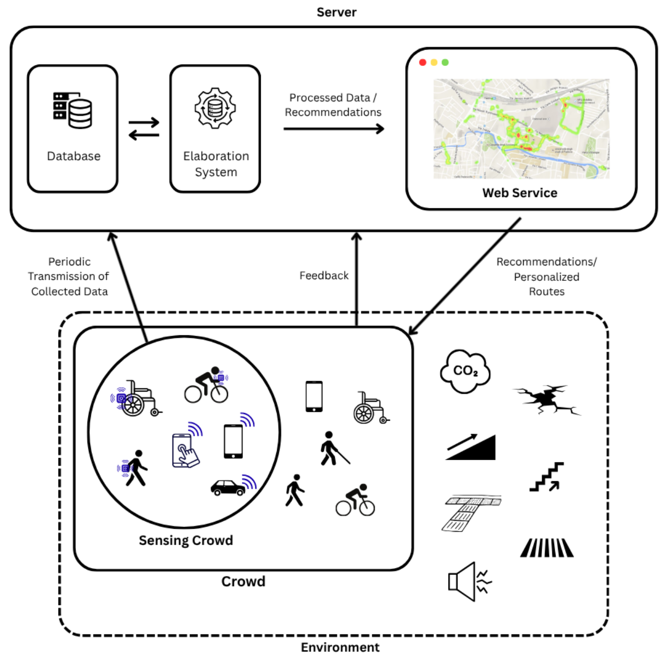

Fig. 1. Collection, processing, and distribution of environmental data and personalized routes through a web services

energy consumption and preserves bandwidth; an essential consideration for user acceptance.

The preprocessed data are then periodically uploaded to a server, where they are stored in a database and further analyzed by an elaboration system. This processing layer can apply different techniques, from simple empirical rules to advanced artificial intelligence algorithms, to extract meaningful information. The resulting processed data and recommendations are then exposed through a web service accessible to the entire crowd. Through this service, users are able to visualize compiled results, such as accessibility maps or recommended routes, and also actively participate with additional information by providing manual feedback. This latter mechanism allows the system not only to provide customized and context-aware recommendations but also to continuously improve thanks to general contributions of the crowd.

Overall, the architecture effectively separates responsibilities: the sensing crowd is responsible for data collection, the preprocessing ensures quality and efficiency, the server ensures large-scale data analysis and storage, while the web service facilitates user interaction and result visualization. This modular architecture supports scalability and simplifies the future integration of additional sensing modalities or analytical methods.

IV. PoC#1: Favorite Route Identification

Several studies in the literature focus on detecting lane surface conditions, traffic levels, and similar environmental factors. However, a more human-centered approach can also be valuable, particularly to support people with mobility impairments. Instead of relying on multiple sensors and complex

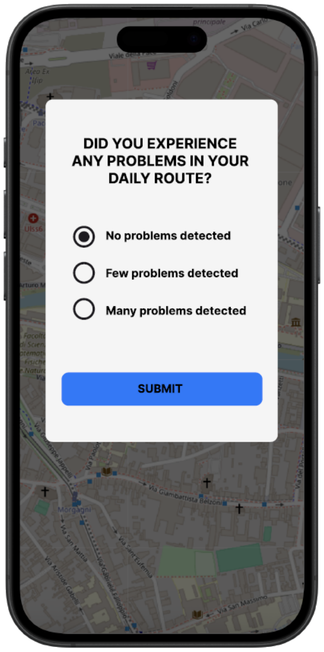

Fig. 2. Prototype feedback form of the PoC#1 application. After completing a daily route, users can report whether the path was problematic, enriching the database with qualitative information that complements GPS-based detection.

solutions, we propose to rely on GPS data to infer the most commonly used and therefore likely accessible routes, passages, bridges, and alleys [23]. In essence, we assume that a person with mobility impairment chooses to use some roads repeatedly if they are adequate to her/his needs, thus indirectly indicating them as accessible. By capturing this information, the system can recommend these routes to other users with similar needs.

A. Mobility Patterns

From an implementation perspective, this requires the construction of a database of frequently traveled paths. A smartphone application can collect this information in the background, relying solely on GPS data, which today consumes much less battery power compared to earlier decades [24].

Such data also provide indirect insights into transportation modes and accessibility. For instance, if the system detects a user consistently traveling at walking or wheelchair speed (3–6 km/h), it can infer that the path is navigable without motorized transport. Conversely, if users regularly avoid geometrically shorter detours, this may suggest the presence of architectural barriers such as stairs, steep inclines, or narrow passages. Furthermore, recurring bus usage along specific routes can indicate that stops on those routes are accessible (e.g., low-floor boarding, ramps, or adequate maneuvering space).

B. System Workflow

The workflow of the application developed for this purpose consists of three iterative stages. Data collection begins after a configurable time threshold or after the user has traveled a certain distance.

A path is initiated when the user moves away from the starting position at a speed consistent with their mobility (e.g., walking or wheelchair speed) and ends when the user stops.

Upon completion, the application determines whether to transmit the route to the remote server. A path qualifies as *frequently traveled* only if it has at least n matches with previously recorded daily routes within a time window of m days. The minimum values of these parameters should be fixed (e.g., 2 and 7) but the system could associate different accessibility levels to a portion of road depending on how frequently that portion of road is used.

Beyond automatic detection, users can explicitly provide feedback on their routes (e.g., whether they were comfortable, accessible, or problematic), as shown in Figure 2. This feedback is attached to the GPS trace, enriching the database with qualitative insights that pure sensor data cannot provide.

Finally, on the server side, the backend eliminates duplicates and stores only new routes.

V. PoC#2: Route Condition Detection

This PoC involves a mobile application that monitors and assesses road conditions in real time. Using the sensors available on smartphones, such as accelerometer, gyroscope, and GPS, the system aims to detect road anomalies such as potholes, cracks, bumps, and uneven pavements, as well as to infer slope and overall surface nature [25]. Unlike more traditional approaches that require specialized hardware or vehicle-mounted equipment [26], this solution takes advantage of widely available devices enabling large-scale deployment through a crowd-sensing approach. In fact, with the latter, we can retrieve a lot of information and make them available to other people who may benefit using a mobile application.

A. Road Anomalies Detection

The detection task involves various surface characteristics and requires multiple sensors. In our solution, the raw accelerometer signals are continuously collected during trips, capturing the vertical and lateral vibrations experienced by the device. To this end, a wheelchair was equipped with an accelerometer to collect acceleration magnitude data that are subsequently analyzed to detect road anomalies that would jeopardize accessibility.

Gyroscope information is also crucial to collect in order to make the measurements more robust. Of course, a normalization and filtering phase is essential to make the measurements reliable and to avoid outliers, anomalies, and false positives.

Concerning slope estimation, it can be derived from the phone's orientation and gravity sensor data, also correlated with GPS elevation. This allows the system to enrich the detected anomalies with contextual information, for example, by identifying whether a bump occurs on an incline or on a flat segment.

Artificial intelligence may significantly improve the detection and classification capabilities of the system. Traditional machine learning methods can classify anomalies on the road

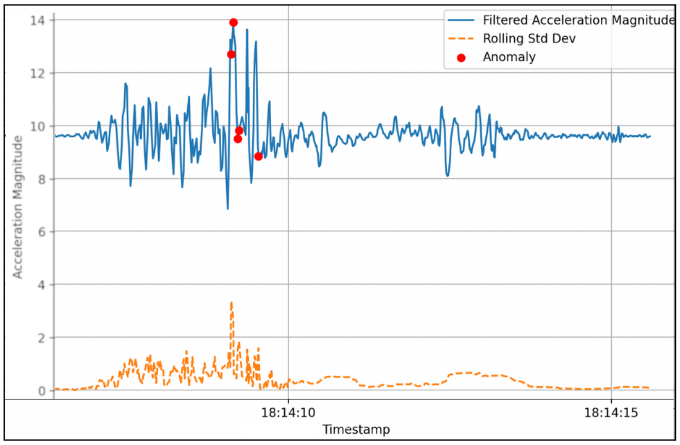

Fig. 3. Data collected through a smartphone mounted on a wheelchair. Detected anomalies (red dots) corresponds to traversing a road bump.

surface based on extracted sensor features, while deep learning approaches offer more sophisticated capabilities. Other deep learning techniques can process raw sensor data and automatically extract relevant features, while the newly built architecture can detect and manage temporal dependencies to distinguish between types of defects, such as potholes, cracks, and speed bumps [27]. Another key advantage of approaches based on artificial intelligence is their ability to continuously learn and adapt from incoming crowdsensed data, progressively refining detection accuracy and expanding the system's capability to recognize anomaly patterns as more users contribute data over time [28].

B. Experimental Assessment

As a case study, we evaluated how obstacles affect accessibility for wheelchair users by analyzing accelerometer data collected during bump traversal, as shown in Figure 3.

The objective of the study was to demonstrate that adverse road conditions can be detected using an accelerometer and pinpointed using GPS to support our system.

A smartphone was mounted on the wheelchair leg, with a seated user weighing about 52 kg. In this setup, we have been able to identify road bumps, potholes, and even distinguish between a curb with an accessible ramp and one without it.

In the tested solution, accelerometer and GPS signals were synchronized with ground-truth video to ensure accurate labeling of events. Acceleration magnitude was used as the primary signal feature and aligned with video timestamps for correct labeling before storing the information in the database. The resulting outputs were compatible with downstream segmentation and integration into map-based services, allowing the representation of accessibility features alongside road surface anomalies.

Mapping curb cuts and slope transitions, together with surface roughness, can provide per-segment comfort and risk scores. This process can be performed automatically through crowdsensed data, but can also be complemented by contributions from individual users or specialized personnel.

TABLE I
CROWDSENSED DATA TYPES AND THEIR RELEVANCE FOR ROUTE CONDITION AND DIFFERENT USER GROUPS.

Crowdsensed Data	**Route Condition Aspect**	**Relevant Users**
Road Surface Quality	Roughness, bumps, potholes	Wheelchair users, people with reduced mobility
Slope Gradient	Inclines and declines	Wheelchair users, people with cardiac or motor impairments
Sidewalk Conditions	Width, smoothness, obstacles	Wheelchair users, people using walking aids
Curb Cuts	Ramps at intersections	Wheelchair users
Tactile Paving	Tactile indicators on sidewalks	Visually impaired users
Obstacles / Construction	Temporary or permanent barriers	All pedestrians

VI. ACCESSIBLE ROUTE GENERATION

Over time, data from multiple users can be aggregated into a comprehensive road condition map, highlighting areas with recurrent issues such as potholes or degraded surfaces. This aggregated data can be visualized through a web interface or a dedicated mobile application that presents layers of informative data. Such a platform can display road surface quality indicators as well as crucial accessibility information for different user groups. For instance, the interface can highlight routes with smoother surfaces suitable for wheelchair users, elderly pedestrians, or parents with strollers. In particular, the system can integrate data on sidewalk conditions, curb cuts availability, tactile pavement for visually impaired users, and the presence of obstacles or construction zones, as summarized in Table I.

Even more interesting, the application uses the gathered data and accessibility-related information to offer customizable route planning features where users can filter paths according to their specific accessibility needs, selecting preferences such as the maximum acceptable surface roughness or quality, preferred slope gradients, or avoidance of certain types of road defects (see Figure 4). Real-time updates and community-driven reporting features would further enhance the platform's utility, creating a dynamic, constantly improving resource for urban accessibility and mobility planning.

VII. CONCLUSION

Our work highlights a critical gap in current urban mapping services, which often fail to address the specific mobility constraints of users with physical impairments. We have demonstrated, through a general architecture and proof-of-concept solutions, that the extraction of distributed collective intelligence provides a viable, scalable mechanism for inclusive navigation. This approach effectively transforms raw environmental data into actionable insights, empowering mobility-impaired individuals to navigate urban spaces with greater autonomy and safety.

Future work will focus on refining data collection models, ensuring data reliability and privacy, as well as the possibility to expand the considered source of information. Indeed, one limit of the presented applications is that they rely on data provided by a minority of the population. Therefore, information, although useful, will not present real time properties (e.g., a curb that is currently crowded of people due to some

Fig. 4. Mobile application interface for PoC#2 illustrating routes conditions. The left screen shows the optimal route from a distance perspective (minimum distance), while the right screen presents the most accessible route. In both views, the route quality is color–coded (e.g., red for mobility-related problems, green for no issues), alert markers highlight specific obstacles such as steep slopes or temporary barriers.

ongoing special event). To address this issue, we need to be able to extract useful accessibility related information even by non impaired citizens. Furthermore, we intend to improve the user interface to enable mobility-impaired individuals to actively participate in shaping the accessibility landscape of their cities.

References

[1] C. Li, R. Y. Pang, D. Labbé, Y. Eisenberg, M. Hosseini, and J. E. Froehlich, "Accessibility for Whom? Perceptions of Mobility Barriers Across Disability Groups and Implications for Designing Personalized Maps," in *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems*, ser. CHI '25, 2025.

[2] R. A. Purba, S. Montagna, and L. Bedogni, "Intelligent healthcare navigation: Personalized path planning with patient condition and environmental awareness," in *Proceedings of the 2025 International Conference on Information Technology for Social Good*, ser. GoodIT '25, 2025.

[3] G. Delnevo, N. Bartolucci, S. Mirri, P. Salomoni, and C. Prandi, "A Mobile Application for the Crowdsensing of Road Pavements Conditions," in *2025 IEEE 22nd Consumer Communications & Networking Conference (CCNC)*, 2025, pp. 1–6.

[4] M. Franco, S. Gatto, M. Noro, L. Perinello, and C. E. Palazzi, "Crowdsensingwayfinding for urban mobility accessibility," in *Proceedings of the 41th ACM/SIGAPP Symposium on Applied Computing*, 2026.

[5] M. Ciman and O. Gaggi, "From a physical system to a pervasive solution to increase people physical activity: Is it possible?" in *2013 IEEE International Conference on Multimedia and Expo Workshops (ICMEW)*, 2013, pp. 1–6.

[6] A. Anjum and M. Ilyas, "Activity recognition using smartphone sensors," in *2013 IEEE 10th Consumer Communications and Networking Conference, CCNC 2013*, 01 2013, pp. 914–919.

[7] S. Choi, R. LeMay, and J.-H. Youn, "On-board processing of acceleration data for real-time activity classification," in *2013 IEEE 10th Consumer Communications and Networking Conference, CCNC 2013*, 01 2013, pp. 68–73.

[8] A. Bujari, B. Licar, and C. E. Palazzi, "Movement pattern recognition through smartphone's accelerometer," in *2012 IEEE Consumer Communications and Networking Conference (CCNC)*, 2012, pp. 502–506.

[9] F. Zambonelli, "Pervasive urban crowdsourcing: Visions and challenges," in *2011 IEEE International Conference on Pervasive Computing and Communications Workshops*, 2011, pp. 578–583.

[10] C. Cardonha, D. Gallo, P. Avegliano, R. Herrmann, F. Koch, and S. Borger, "A crowdsourcing platform for the construction of accessibility maps," in *Proceedings of the 10th International Cross-Disciplinary Conference on Web Accessibility*, ser. W4A '13, 2013.

[11] C. Prandi, G. Delnevo, P. Salomoni, and S. Mirri, "On Supporting University Communities in Indoor Wayfinding: An Inclusive Design Approach," *Sensors*, vol. 21, no. 9, 2021.

[12] A. Arenghi, S. Belometti, F. Brignoli, D. Fogli, F. Gentilin, and N. Plebani, "UniBS4All: A Mobile Application for Accessible Wayfinding and Navigation in an Urban University Campus," in *Proc. of the 4th EAI International Conference on Smart Objects and Technologies for Social Good*, 2018, p. 124–129.

[13] AccessibleMaps, "AccessibleMaps," Available from: http://www.accessiblemaps.org/, 2009, [Accessed: October 2022].

[14] C. Prandi, P. Salomoni, and S. Mirri, "mPASS: Integrating people sensing and crowdsourcing to map urban accessibility," in *2014 IEEE 11th Consumer Communications and Networking Conference (CCNC)*, 2014, pp. 591–595.

[15] S. Mirri, C. Prandi, P. Salomoni, F. Callegati, and A. Campi, "On Combining Crowdsourcing, Sensing and Open Data for an Accessible Smart City," in *2014 Eighth International Conference on Next Generation Mobile Apps, Services and Technologies*, 2014, pp. 294–299.

[16] E. Buza, S. Omanovic, and A. Huseinovic, "Pothole detection with image processing and spectral clustering," in *Proceedings of the 2nd International Conference on Information Technology and Computer Networks*, vol. 810, 2013, pp. 48–53.

[17] C. Wu, Z. Wang, S. Hu, J. Lepine, X. Na, D. Ainalis, and M. Stettler, "An Automated Machine-Learning Approach for Road Pothole Detection Using Smartphone Sensor Data," *Sensors*, vol. 20, no. 19, 2020.

[18] S. Sattar, S. Li, and M. Chapman, "Road Surface Monitoring Using Smartphone Sensors: A Review," *Sensors*, vol. 18, no. 11, 2018.

[19] X. Li, D. Huo, D. W. Goldberg, T. Chu, Z. Yin, and T. Hammond, "Embracing Crowdsensing: An Enhanced Mobile Sensing Solution for Road Anomaly Detection," *ISPRS International Journal of Geo-Information*, vol. 8, no. 9, 2019.

[20] V. Astarita, M. V. Caruso, G. Danieli, D. C. Festa, V. P. Giofrè, T. Iuele, and R. Vaiana, "A Mobile Application for Road Surface Quality Control: UNIquALroad," *Procedia - Social and Behavioral Sciences*, vol. 54, pp. 1135–1144, 2012.

[21] M. Furini, S. Mirri, M. Montangero, and C. Prandi, "Privacy Perception when Using Smartphone Applications," *Mob. Netw. Appl.*, vol. 25, no. 3, p. 1055–1061, Jun. 2020.

[22] N. Lane, E. Miluzzo, H. lu, D. Peebles, T. Choudhury, and A. Campbell, "A survey of mobile phone sensing," *Communications Magazine, IEEE*, vol. 48, pp. 140 – 150, 2010.

[23] C. E. Palazzi, L. Teodori, and M. Roccetti, "Path 2.0: A participatory system for the generation of accessible routes," in *2010 IEEE International Conference on Multimedia and Expo*, 2010, pp. 1707–1711.

[24] A. Grenier, E. S. Lohan, A. Ometov, and J. Nurmi, "A Survey on Low-Power GNSS," *Commun. Surveys Tuts.*, vol. 25, no. 3, p. 1482–1509, Jul. 2023.

[25] M. Nenadic, C. E. Palazzi, and A. Zanella, "Road accessibility mapping through smartphone-based sensing," in *Proceedings of the 40th ACM/SIGAPP Symposium on Applied Computing*, 2025, p. 11–18.

[26] A. V. Kumar, "Pavement surface condition assessment: a-state-of-the-art research review and future perspective," *Innovative Infrastructure Solutions*, vol. 9, no. 12, p. 470, 2024.

[27] L. Cheng, X. Zhang, and J. Shen, "Road surface condition classification using deep learning," *Journal of Visual Communication and Image Representation*, vol. 64, p. 102638, 2019.

[28] I. Ferjani and S. A. Alsaif, "Dynamic Road Anomaly Detection: Harnessing Smartphone Accelerometer Data with Incremental Concept Drift Detection and Classification," *Sensors*, vol. 24, no. 24, 2024.