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Mobile crowdsensing for road sustainability: exploitability of publicly-sourced data

Lorenz Cuno Klopfenstein ^a, Saverio Delpriori ^a, Paolo Polidori^b,
Andrea Sergiacomi^c, Marina Marcozzi^c, Donna Boardman^d, Peter Parfitt^d
and Alessandro Bogliolo ^a

^aDiSPeA, University of Urbino, Urbino, Italy & Digit srl; ^bDiGiur, University of Urbino, Urbino, Italy & Digit srl;
^cRegione Marche, Informatica e Crescita Digitale, Ancona, Italy; ^dBuckinghamshire County Council,
Aylesbury, UK

ABSTRACT

This paper examines the opportunities and the economic benefits of exploiting publicly-sourced datasets of road surface quality. Crowdsourcing and crowdsensing initiatives channel the participation of engaged citizens into communities that contribute towards a shared goal. In providing people with the tools needed to positively impact society, crowd-based initiatives can be seen as purposeful drivers of social innovation from the bottom. Mobile crowdsensing (MCS), in particular, takes advantage of the ubiquitous nature of mobile devices with on-board sensors to allow large-scale inexpensive data collection campaigns. This paper illustrates MCS in the context of road surface quality monitoring, presenting results from several pilots adopting a public crowdsensing mobile application for systematic data collection. Evaluation of collected information, its quality, and its relevance to road sustainability and maintenance are discussed, in comparison to authoritative data from a variety of other sources.

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Collective intelligence; data collection; data privacy; mobile crowdsensing; road quality measurement

1. The impact of road infrastructure

In the eyes of the average driver, roads are little more than smooth surfaces for vehicular traffic and they seldom deserve deeper consideration, unless their quality degrades and directly impacts the driver's comfort. Nonetheless, roads are complex artifacts, built with a set of diverse layers, with materials that are accurately selected based on national or regional specifications (Huang 1993). Moreover, road infrastructure provides essential services to society as a whole. Roads provide the backbone for national and international socio-economic development, empower economic activities, drive commerce, enable the transport of passenger and freight. In general, a country's road network can be considered its most important public asset (Nicodème 2015). The full reconstruction cost of the European road network alone – totaling 6.6 million kilometers – can be estimated at over 8 000 billion Euros (European Union Road Federation 2014).

According to a 2017 survey by the EU Road Federation, across all EU 28 countries, more than 72% of inland passenger transport relies on private vehicles and 49% of

goods are transported on road infrastructure exclusively, followed by maritime transport (31.8%) and railways (European Union Road Federation 2017). Roads also contribute significantly to a country's domestic product: they can be estimated to be responsible for up to 20% of a nation's GDP, when considering fuel, vehicle maintenance, road maintenance, and all related services (World Road Association 2014). Robust infrastructure has also been shown to have a positive effect on the establishment of manufacturing industries, significantly increasing the appeal of municipalities close to major motorways in the eyes of investors (Holl 2004). Public investment in road transport on average has positive impacts on total productivity of the transport-using sector, agglomeration effects (especially in the services sector), and other wider economic benefits (Crafts 2009). These results are confirmed by recent country-level surveys, which also positively gauge the effect of improvements to road networks. In Britain, improvements to motorways correlate with better employment, wages, and number of commercial establishments (Gibbons et al. 2019). Similar effects were observed in an analysis of economic growth in Mexico (Duran-Fernandez and Santos 2014) and in China (Banerjee, Duflo, and Qian 2012), with improved regional development, higher output per worker, and higher per capita GDP levels. While economic development is a dynamic process that cannot be assessed solely on the basis of one factor, the development of hard infrastructure such as roads is widely recognized to be quintessential to the viability of industries and the development of a growing economy, in particular in developing countries (Yifu 2012).

Nonetheless, over the last decades, investment in transport and road infrastructure has been stagnating: after reaching 1.5% of GDP on average, it has been decreasing since the 1970s (Konstandinos 2017). According to the European Investment Bank, less than a quarter of infrastructure investments are aimed at roads, while 45% of investments target the railway system (European Union Road Federation 2017). While long-term social and environmental effects can be cited in favor of non-road-based means of transportation, road investments have been shown to yield a far higher return on investment if compared with improvements to the railway network, which are considerably more expensive and often privately owned, as with the UK (Affuso, Masson, and Newbery 2003). Moreover, subsidies to railway transport at the expense of road investments arguably may not lead to compelling results, since road transport shows limited substitutability and there is evidence of much complementarity between the two transport modes in the majority of non-exclusively urban scenarios (Productivity Commission 2006). A lack of investment in strategic road networks has far reaching impacts: warnings given by authorities in 2009 (AASHTO 2009) – citing lack of funding and the degradation of roads in the United States, a quarter of which were found already to be in an insufficient state – were followed by a negative assessment in 2017 by the American Society of Civil Engineers (ASCE), assigning an overall 'poor' grade (D–), based on current status, capacity, and future outlook (American Society of Civil Engineers 2017).

Lacking infrastructure has effects on society that are not limited to economic development: in developing countries and in less densely populated areas, inadequacies of the road network can be an impediment to essential services such as access to hospitals, schools, and even water (Nicodème 2015). Also, according to statistics collected on the US road network, more than half of driving fatalities and

more than 30% of all car crashes are due to poor road conditions. Overall costs of accidents due to bad roads surpass those of accidents due to other causes, such as speeding or driving under the influence (T. R. Miller and Zaloshnja 2009). In addition to the cost of crashes and accidents, poor roads cause higher vehicle operating costs (VCO), i.e. more frequent maintenance, higher fuel consumption, noise, and pollution. Most of these costs are borne by road users: a 2012 study, based on fuel and vehicle operating cost models in Zaniewski et al. (1982), found that user costs increase dramatically on poor roads and they far outweigh agency costs due to road maintenance. Investment in better road maintenance entails a 50-fold return on investment in terms of savings for users (Islam and Buttlar 2012). The World Bank reports that ‘every dollar of delayed road maintenance expenditure increases vehicle operating costs by between two and three dollars’ (Heggie and Vickers 1998).

1.1. Road maintenance

Operations of road maintenance are of paramount importance in ensuring that infrastructure conditions are kept at an acceptable level. They can be categorized into ‘routine’ works, limited to weekly or monthly small-scale operations with the purpose of cleaning or patching the road’s surface or fixing smaller potholes; ‘periodic’ works, that are planned in order to preserve the road’s structural integrity; and ‘urgent’ work, usually performed in response to natural calamities or unforeseen events (Burningham and Stankevich 2005). Based on an estimate by The World Bank in 2000, the cost of routine maintenance per kilometer can typically be between 200 and 1,500 USD per year (World Bank Rural Transport Thematic Group 2003), with an average of ca. 500 USD (Burningham and Stankevich 2005). However, many countries have budgets that do not fully cover these routine maintenance expenses: lack of funding in this case jeopardizes past construction investments.

The main principle supporting the need for timely road maintenance is that spending money now avoids much higher costs in the future. It has been argued that ‘1€ spent on early road maintenance prevents spending up to 15€ in rehabilitation and reconstruction’ (European Union Road Federation 2014). Investing in early road maintenance prevents future spending in repairs and road reconstruction, while inadequate maintenance places undue financial and societal burden on future generations (Nicodème 2015). An annual report by the South African National Roads Agency found that maintenance costs multiply 6 times after 3 years of neglect and they can further skyrocket to 18 times the original maintenance costs after 5 years (SANRAL 2016). On the other hand, every invested dollar ensures savings of around 4 dollars on the economy, when summing future reparations and user costs (Foster and Briceño-Garmendia. 2010). Similar figures are reported by US highway authorities, indicating that the cost of full reconstruction amounts to 3 times the total cumulative cost of periodic maintenance (AASHTO 2009). Following a more theoretical approach, results of a study based on a Markov-based model of road degradation and maintenance operations also showed that more frequent maintenance significantly decreases the cost to road users and thus minimizes the road’s overall life-cycle cost (Gao and Zhang 2013).

1.2. Monitoring road quality: techniques and costs

Efficient road asset management requires periodical surveys of the roads and regular monitoring and maintenance operations. These are costly, lengthy, and often inefficient processes that usually encompass visual inspections by experts and the use of specially equipped vehicles. Surveys focus on properties such as road surface evenness (transverse or longitudinal), surface defects (cracking, potholes, depressions, delamination, patches, etc.), and vehicle/road interactions (irregularities in road surface texture, wheel friction, noise, rolling resistance, etc.). Some of these measures are collected using standard and objective parameters, such as the International Roughness Index (IRI) (Sayers, Gillespie, and Queiroz 1986), or standardized pavement rating scales, such as the PASER scale based on visual evaluations (Walker 2002). Road quality properties can be measured with special automated tools mounted on standard vehicles – including 3D laser measuring systems, 2D line scan cameras, laser profilometers – or with highly specialized vehicles that measure friction, wheel slip, or noise. Road inspections are however most often performed by maintenance operators on site with mechanical tools or with simple visual examinations (J. S. Miller and Bellinger 2014; World Road Association 2016).

In practice, road maintenance operations commonly rely on a combination of different techniques, including a) visual inspection of the road surface; b) road surveys with subjective annotations (start/end of damaged or degraded sections, spot defects, potholes, etc.) and collection of video evidence; c) aerial photos (chorographies); d) instrumental tests using specific tools, including vehicles equipped with infrared IRI measurement instruments, road surface scanning technology, or the extraction of road surface samples through core drilling. However, since most of these instrumental tests have very high costs, they all require specialized personnel, and some can be quite invasive, most extensive road monitoring surveys are only performed on an annual basis. In-depth inspections are often performed only for short road stretches or when evaluating newly paved roads. In countries such as England and Wales, periodical road condition surveys are mandated at a national level and performed by local authorities on an annual basis. The periodical survey includes both a Coarse Visual Inspection (CVI) and a more in-depth analysis of the strategic road network (which includes properties such as transverse rut depth, longitudinal profile variance, and road texture analysis, among others). The survey produces a Road Condition Indicator (RCI) which is used to roughly classify roads into one of 3 categories: roads in good state, deteriorated roads that should be investigated to determine the optimum time for planned maintenance, and poor roads that are likely to require planned maintenance within a year. RCI values from the survey are used to determine maintenance priorities and to interpret and predict road surface conditions at a national level (Klopfenstein et al. 2018b). Similarly, a recent study by Laubis et al. reports that the federal road network in Germany is fully monitored at 4-year intervals. These survey however often do not cover all lanes of larger roads. County and municipality-level roads are monitored with subjective methods only, based on manual pen and paper annotations, and thus have no national uniformity (Laubis et al. 2018). Methods available to urban and local road agencies present obvious issues in terms of repeatability and reliability, since they mostly rely on subjective evaluations.

Road monitoring operations impact the total maintenance cost of the road network: extensive visual inspection surveys performed by skilled technicians, using software to geographically annotate degraded road sections, potholes, and other road elements, can cost between 20 and 40 € per kilometer. More in-depth surveys, including roadway width, crossings, and signal inventories, can cost up to 160 € per kilometer¹.

Because of its extent, it is usually unrealistic to use traditional methods to survey a country's entire road network. Road infrastructure monitoring is usually performed with sufficient frequency only on major road sections. The lack of up to date and reliable information on road conditions provides an additional obstacle to providing adequate road maintenance services.

In this paper we examine the opportunity of a road monitoring approach based on public datasets of road surface quality, sourced from collective and open initiatives. Mobile crowdsensing approaches for 'bottom-up' digital social innovation and public asset management are discussed in Section 2. Test deployments, results, data validation approaches, and comparisons with authoritative sources are discussed in Section 3, based on previous work on road quality data collection (Klopfenstein et al. 2018b). Section 4 concludes with a discussion of the possible impact of these solutions and integration with traditional road maintenance methods. Common issues of crowdsensing systems, such as providing incentives to drive user adoption, data ownership, data privacy, and accuracy of the system, are also presented and discussed.

2. Social contributions: the grassroots approach

Crowdsourcing is a distributed problem-solving model that 'harnesses the creative solutions of a distributed network of individuals through what amounts to an open call for proposals' (Brabham 2008). Crowdsourcing-based systems rely on a central entity or institution sponsoring such an 'open call for proposals' and a large network of individuals ready to contribute, often in exchange for a bounty or other forms of reward. Such systems depend on the so-called *wisdom of the crowd*, according to which 'groups are remarkably intelligent and are often smarter than the smartest people in them' (Surowiecki 2005). The coordination of these distributed systems – nowadays enhanced through the use of innovative technologies – gives rise to *collective intelligence*, an emergent property of large groups of people that enables them to perform more effectively than a lone individual (Malone, Laubacher, and Dellarocas 2009). While this capacity of groups to assemble and coordinate expertise and resourcefulness is not uniquely related to modern information and communication technologies, the introduction of these advances greatly enhances a group's ability to solve problems and to create new knowledge asynchronously or at a distance.

As a system of driving talent, time, and effort from a large group of people towards one shared goal, crowdsourcing has been employed successfully for several different purposes, such as funding projects, gathering ideas, developing designs, or collective writing and editing endeavors, as in the case of Wikipedia (Kittur and Kraut 2008). *Collective intelligence* has been found in groups of heterogeneous individuals for predictions and other menial tasks, such as forecasting the results of a political election or counting the number of beans in a container (Sunstein 2006). Online crowd-based systems have also shown to be effective at coordinating very large groups of people,

focusing on complex tasks that may require some form of self-organization or leadership (Kittur, Lee, and Kraut 2009).

These systems share basic traits that are common in innovative organizations: high autonomy of participants, sharing of diverse skillsets, and mostly flat hierarchies. It may appear possible to harness the same collective intelligent behavior of large groups to drive social innovation and to challenge seemingly intractable social problems as well. However, as Tjornbo argues, online collective intelligence shows serious limitations when applied to these fields: groups quickly become polarized when handling issues of political nature and struggle with problems that require complex coordination (Tjornbo 2016).

2.1. Mobile crowdsensing and applications for road quality

Crowd-based paradigms provide a good fit for various kinds of data collection tasks, in the form of systems for ‘participatory’, ‘people-centric’, or ‘crowd’ sensing. These collective intelligence systems rely on data and local knowledge contributed by users in the scope of a large data collection campaign (Guo et al. 2014). In this scenario, data collection tasks performed by individual contributors are usually menial in nature or can be automated by a data gathering device, while coordination is managed centrally by the crowdsensing system. This matches the ideal type of application of collective intelligence: a problem that is ‘intellective’ in nature – i.e. having clear cut answers and making it easy to distinguish between correct and wrong contributions – and that requires ‘low coordination’ – i.e. each participant can work independently, without tight coordination needs between users. Central coordination ensures that users require weak links or no links at all between them. These conditions, which match those in ‘participatory’ or ‘citizen’ science, are ideal for scaling the approach to very large numbers of participants (Nov, Arazy, and Anderson 2014).

Data collection at a similarly large scale, especially in an outdoor or urban environment, has traditionally made use of conventional sensing technologies such as wireless sensor networks (WSN). However, these technologies often encounter difficulties with real-world installations, such as limited coverage and high installation or maintenance costs (Liu et al. 2013). Mobile crowdsensing systems on the contrary take advantage of nearly ubiquitous mobile devices, including modern smartphones and *Internet of Things* devices, which frequently provide multiple on-board sensors and advanced computation capabilities, thus laying the ground for the development of inexpensive and efficient large-scale data collection campaigns. These systems provide ‘a new sensing paradigm that empowers ordinary citizens to contribute data sensed or generated from their mobile devices and aggregates and fuses the data in the cloud for crowd intelligence extraction and human-centric service delivery’ (Guo et al. 2015).

Over the course of the last years, smartphone-based data collection has become increasingly popular. Many proposals for a crowdsensing road anomaly detection system exist in literature, usually through 3D reconstruction, vibration analysis, or vision-based pavement crack monitoring (Sattar, Li, and Chapman 2018). If built to scale, mobile crowdsensing can be exploited as a low-cost solution to detect road surface anomalies in a timely fashion and thus constantly monitor infrastructure quality.

One of these systems, the *SmartRoadSense* crowdsensing platform (SRS hereafter), has been developed with the purpose of performing quantitative evaluations of road

surface roughness using consumer-grade accelerometer data from smart-devices (Alessandroni et al. 2014). As shown in Figure 1, the system's main component is a smartphone app that is installed and runs on the user's mobile device. The device is anchored to the driver's vehicle, ideally through the use of a rigid smartphone bracket. While traveling, the app collects raw data from accelerometers and GPS, thus producing geo-referenced estimates of road roughness in real time, according to a mathematical model based on signal processing methods. Results are computed in terms of dimensionless units, known as PPE (defined as the 'power of prediction error' as determined by its signal processing model). The resulting data is transmitted to a cloud-based service, which provides map matching and aggregation, and produces an aggregate visualization of the road network's surface quality. The resulting data is published as open data (Klopfenstein, Delpriori, and Bogliolo 2018) and displayed on an interactive online map, using a color scale (from dark green to red) overlaid on cartographic data from OpenStreetMap (Freschi et al. 2014).

2.2. Active citizenship for road maintenance

Public infrastructure management, public asset monitoring, and road transport sustainability, along with all previously discussed societal issues derived from lack of adequate infrastructure, are societal challenges that are experienced across nations and are well beyond personal control, even if they have a very direct impact on individuals and local contexts. Participatory systems, approaching these issues thanks to citizen engagement, broaden existing notions of citizenship and develop innovative practices that can contribute towards sustainability (McCrorry, Veeckman, and Claeys 2017). Citizen science has a long history of being a meeting point between citizens and experts: modern tools further strengthen this bound, allowing citizens to directly contribute to processes of enquiry and, in return, to learn about what is being observed (Bonney et al. 2009). Furthermore, the flip in information access and flow encourages fuller understanding and awareness of the studied phenomena,

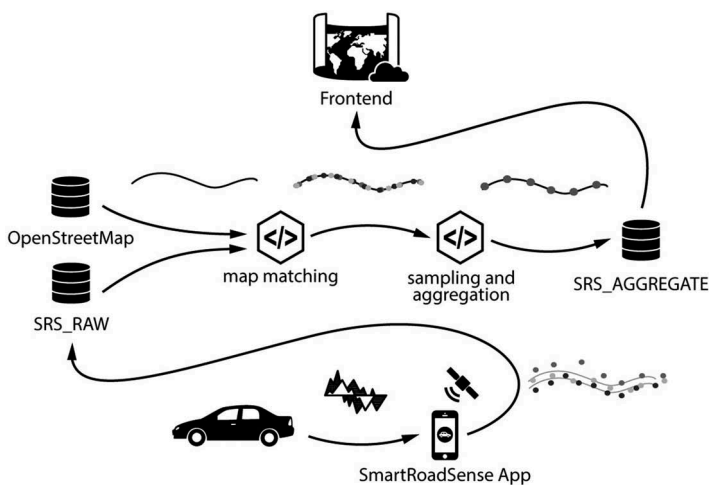


Figure 1. Architecture overview of the road quality crowdsensing system.

eschewing top-down information filtering and organization. Collective assessment of issues makes them accessible and understandable by end-user communities, instead of restraining them to selected stakeholders, channeling users as an important source of innovation and knowledge (Bloch 2007). Open, participatory-oriented systems, based on socio-technical solutions, become the empowering infrastructure for action in the face of societal challenges. The ‘bottom up’ development and exploitation of innovative solutions that benefit society, address social needs, and adopt modern ICT tools, drives *user-driven* and *digital* social innovation (Arniani et al. 2014). Citizen engagement and public participation are in fact paramount in building trust in public institutions, driving the public decision-making process, and encouraging community and individual empowerment. In the context of social innovation, the involvement of active citizens also provides initiatives with the required legitimacy (TEPSIE 2014).

Citizen-sourced actions, such as crowdsourcing and crowdfunding, can be seen as the simple results of budget cutting policies affecting a field. Case in point: lacking road transport infrastructure. In this context, crowd-based systems perform an arguably compensatory function and thus cannot be seen as viable innovation sources *per se*. (Anheier, Krlev, and Mildenerberger 2019). Similarly, a risk expressed by the European Commission, is to confine social innovation processes to bottom-up initiatives. Social innovation does not necessarily stem from micro-level or grassroots initiatives, but it can emerge from sharing and networking between a variety of actors, possibly leveraging the aforementioned bottom-up support (Therace, Hubert, and Dro 2011). Social innovation practice and analysis have often focused on development of the local territory, because of its tight bond with close communities and dense human interactions, where dynamics of decline, revalorization, hope, and innovation are more easily identifiable. Institutions for participation, decision-making, and community empowerment that are backed by ‘bottom-up’ movements give back agency to citizens, both articulating the basic needs of the local community and giving power to local policy-makers (Moulaert 2009).

In this scenario, the contribution of crowdsensing campaigns and their social reach can be instrumental to the attainment of more effective local public asset management, including road maintenance operations. Likewise, crowdsensing instruments that promote positive social changes can be understood as the technical stepping stone on which ‘collective awareness platforms’ are based: while the underlying technology must be designed to take into account existing policies, regulations, and systems, it can also be the pivot of user-generated information, public agency, and awareness, all of which can expand the base of interest and channel bottom-up activities. These instruments help shape a formal layer, composed of policies and regulations, and an informal layer that represents the cultural and societal aspects, in terms of shifting attentions and community awareness (Arniani et al. 2014).

In the next section we present results from crowdsensing-based road quality campaigns using *SmartRoadSense*, discussing data validation and exploitation approaches that confirm the practicality of the citizen-based data collection approach for public asset management initiatives such as road monitoring.

3. Exploitability of data from public road sensing pilots

A set of data collection pilot projects launched over the course of the past three years provide an example of real-world road quality data collection experiments, including national level pilots and smaller deployments that target a single regional or municipal entity. These pilots were activated within the CROWD4ROADS² project, a digital social innovation initiative that aims to get drivers involved in road transport sustainability, and they were managed locally by a project partner. Each pilot was bound to a geographical area and combined the public release of the *SmartRoadSense* mobile application with communication campaigns and support by local authorities.

The complete list of pilots and the total amount of data collected by July 2018 is listed in Table 1. The table includes the count of raw data points (r), the raw road quality estimate measured by SRS on the user's device, at a rate of 1 measure per second; count of aggregated points (a), each of which is produced by the SRS back-end service and represents the aggregated road quality estimate of approximately 20 meters of road; the number of mapped kilometers (m), that is the length covered by aggregated points (i.e. $m = a \times 20m$); the percentage of covered road network (p) in relation to the total road network length of the pilot's area; and the mapping redundancy (rd), that is the average number of raw data points that contribute to the same aggregated road quality point (i.e. $rd = r/a$).

The Italian pilot was launched in 2016, after a year of internal beta testing, and covers the entirety of the Italian road network, which includes more than 650,000 kms of roads. Graphically, the status of the national pilot is shown in Figure 2. Marche is a region in central Italy that extends over an area of 9,694 sq. kms and has a population of approximately 1.5 million people. Existing roads, at region and province level excluding highways and national roads, cover approx. 5,835 kms. The pilot covers the entirety of the region. Ancona, a major seaport on the Adriatic Sea, is capital of the Marche region and has been adopted as a city-level pilot: adoption of SRS was promoted in particular through the endorsement by the municipality and the region, usage by public transport companies and employees of municipal entities, and communication campaigns in relation to large touristic events on the territory.

An additional city-level pilot was started on 5 June 2018 in the municipal area of Mantova (capital of the Mantova province in the region of Lombardia, northern Italy) and ended on 1 August 2018. During traditional road monitoring work, performed by a local road technician through visual inspection, SRS was deployed to effectively compare collected data.

Buckinghamshire is a county in South East England that extends over an area of 1,874 sq. kms and includes a road network of about 3,500 kms. In addition to

Table 1. Data collected by *SmartRoadSense* pilots (up to date as of 20 July 2018).

Pilot	Raw (r)	Aggregated (a)	Mapped kms (m)	% (p)	Mapping redundancy (rd)
Italy ^a	11,433,700	2,374,872	47,497.44	7.0	4.81
Marche ^b	5,094,730	237,737	4,754.74	81.4	21.43
Ancona ^c	163,610	12,622	252.44	72.1	12.96
Mantova ^c	372,943	12,419	248.38	22.1	30.03
Buckinghamshire †	2,172,280	84,666	1,693.32	51.5	25.66
Total	21,792,958	2,809,776	56,195.52	–	7.76

^aCountry-level pilot. ^bRegion-level pilot. ^cCity-level pilot.

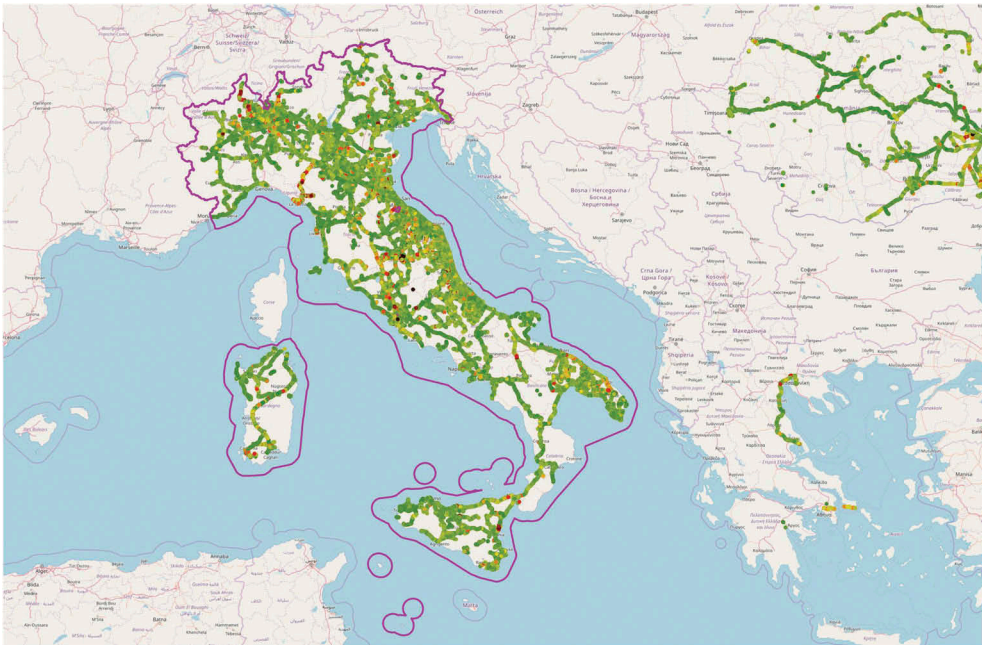


Figure 2. Italian pilot overview.

promoting the adoption of SRS through events and workshops by the County Council, SRS was systematically adopted by county council employees during their working day. While the total amount of mapped kms covers half of the road network, the systematic adoption for routine journeys has ensured a very high mapping redundancy.

3.1. Data validation approaches and deployment analysis

Mobile crowdsensing as a paradigm enables the collection of large quantities of data over a relatively short time span and with limited cost. Scenarios where low-cost ubiquitous sensors can be used to have an indirect measurement of the target physical property, as is the case of smartphone accelerometers monitoring road quality in SRS, are particularly well-suited scenarios because users require no additional equipment to participate. Adoption of crowdsensing initiatives can be reinforced with campaigns promoting their adoption, as in many of the pilot projects described above. They especially benefit from the systematic adoption by users that can routinely collect data (such as road maintenance operators or bus and taxi drivers in the case of SRS), as shown by the coverage of city-level pilots in [Table 1](#).

However, crowdsensing initiatives that attempt to collect object data about physical properties are susceptible to the collection of low quality data for a number of reasons: a) the measurement process can inherently be imprecise or prone to interferences, depending on the kind of physical quantity measured; b) measurements are subject to systematic and random errors due to the quality of adopted sensors (especially when using low-cost embedded sensors in consumer grade electronics), which can be faulty or uncalibrated; c) users can be unreliable or malicious, and may intentionally collect

altered or fake data; d) aggregation of measurements in terms of where and when they were recorded is inherently constrained by the limited temporal and spatial accuracy of the measurement system and can be impacted by conflicting information by a multitude of users (Freschi et al. 2017). In fact, during a small-scale trial in 2011 many participants in a crowdsensing experiment explicitly expressed distrust in data by fellow users, feeling that some of them would maliciously generate bad data (Zimmerman et al. 2011).

With traditional data collection technologies, such as WSNs, it is usually possible to define the usefulness of harvested data, in the form of a Quality of Information (QoI) index (Bisdikian, Kaplan, and Srivastava 2013), but the same notions cannot be applied as easily in a crowdsensing scenario. Guaranteeing something akin to a QoI level for user supplied data must inherently take into account the bias introduced by human users and the impact of their dynamics and behaviors during the data collection process. Several proposed mechanisms are based on a form of user reputation, where behaviors and data that deviates from those of other contributions is punished or where trust is accumulated based on previous contributions (Yu et al. 2014). Mobile crowdsensing, where movement of users is inherently tracked during data collection, can factor in the regularity of movement patterns to determine each user's authority in a certain area (Mashhadi and Capra 2011). Various solutions have been reported in the literature with different limits and weaknesses (Restuccia et al. 2017). The collection of significant road quality data, as performed by SRS, encounters the same difficulties of crowdsensed data in general mentioned above. In addition, SRS relies on an indirect measurement – i.e. processed accelerometer data as an index of road surface quality – and there is no uniquely accepted road quality index that can be directly used as ground-truth data.

Several approaches for data validation have been adopted during the development of SRS and the implementation of the pilots mentioned above, in order to verify the quality of the collected data, its statistical significance, and its correlation with real ground-truth data (where available), with the intent of making the output of SRS suitable as a replacement or a valuable addition to traditional road surface monitoring operations (Klopfenstein et al. 2018b). Deployment mode and results cannot be generally compared between different pilots. However, each pilot provides an independent opportunity of verifying the data collection approach, ensuring that sufficient coverage is attainable, and that road roughness data can be validated against ground truth data.

Details and results from data validation initiatives, performed in the context of previously mentioned local pilots, are described in the following subsections.

3.1.1. Marche region deployment

This first approach of data validation was applied during the first months of 2017, by performing a thorough visual inspection of sections of the local regional roads in the Marche region (in the 'Strada Provinciale' category, SP502 and SP362 in particular). At the same time, SRS was deployed with a standardized setup (Samsung S4 mobile phone, running Android 5.0 and SRS 3.1, phone attached to rigid bracket and hooked to the front windshield with a suction cup) and systematically travelling on the roads selected for examination (all road sections should have at least two measurements, one for each traveling direction). Visual inspection data (gathered in the form of written reports by

road maintenance experts and relevant photographs of damaged road sections, annotated with their position) were then compared with the aggregated SRS data.

Feedback by the road maintenance experts mentioned that in general, visual observations were coherent with aggregated SRS data. However: a) visual inspection of the road does reveal phenomena (such as local depressions, landslides on the road sides, sloping road surface, imperfections at the lane center, etc.) that do impact road status and driving comfort but that do not generate accelerations that can be detected by SRS; b) aggregated data points represent the average quality of 20 meters of road, which may mask smaller potholes or punctual damage to the road surface.

3.1.2. Buckinghamshire deployment

This data validation approach was applied in July 2018, by performing a thorough visual inspection of sections of the highway network in the county of Buckinghamshire (specifically within the Amersham and Aylesbury areas). At the same time, SRS was deployed with a standardized setup (iPad Air 2 tablets, running iOS 10.2, and SRS 3.1, tablet placed on a non-slip mat on the vehicle dashboard; Samsung Galaxy S6 mobile phone, running on Android 7.0, and SRS 3.1, mobile placed in a bag in the passenger footwell) and systematically travelling on the selected roads to examine (all road sections had at least two measurements, one for each carriageway direction). Defect reports, visual inspection data (gathered in the form of written reports by highway inspectors and technicians, and relevant photographs of road sections, annotated with their position) were compared with the aggregated SRS data.

Feedback by the highway inspectors and technicians where consistent with previous observations within the Marche Region deployment. A collection of ‘degraded’ road sections was selected by the highway technician performing the inspection (i.e. roads that show some amount of damage that will require planned maintenance), together with non-degraded sections from the same dataset. SRS road roughness data for these sections was extracted and analyzed, yielding the results shown in [Table 2](#): average and standard deviation of road roughness values significantly increase on degraded road sections, showing that SRS data can be used as a reliable indicator of the road’s condition (Klopfenstein et al. 2018b).

3.1.3. Mantova deployment

The third proposed validation approach has been developed thanks to a pilot in the municipal area of Mantova, which started on 5 June 2018 and was concluded on 1 August 2018. The data collection pilot was executed by a road technician with the task of systematically performing the visual inspection of the complete road network of Mantova’s municipal area and province. This inspection was performed by slowly

Table 2. Analysis of aggregated road roughness values per road section type.

	Non-degraded sections	Degraded sections
Aggregated points count	29	24
Road roughness average	0.192	0.654
Road roughness standard deviation	0.004	0.135
Maximum road roughness	0.533	2.395
Minimum road roughness	0.052	0.313

driving along all roads (at an average of 30 km/h) and annotating significant ‘events’ through a specialized software application. The application would continuously collect the vehicle’s geographical position (through GPS) and record pictures of the road (through two webcams mounted on the windscreen). Events annotated by the technician include a) the start and end of degraded road sections; b) the presence of potholes or other surface defects; c) vertical signage; d) milestones; e) car or pedestrian crossing. Results of the survey were produced as documents listing all collected events, annotated with photos and location.

At the same time, a Moto G 4 smartphone running Android 6 and SRS 3.1.3 was rigidly mounted to the windscreen of the same vehicle, using a bracket on a suction cup. The app was configured to record continuously, thus progressively covering the whole road network of Mantova and often recording the same road section multiple times. Results from one recording track on the intersection between SP18 and SP19, recorded on 27 June 2018, have been analyzed in detail and compared with raw and aggregated results from SRS.

Survey results collected on 27 June 2018 were analyzed and compared to SRS data collected on the same day. Based on manual marks supplied by the road technician, road sections were split into 3 categories: non-degraded roads, degraded roads, and road sections with potholes (or other surface defects). Results of the road roughness data analysis are shown in Table 3, indicating how different road types show significantly different average and standard deviation values in terms of measured road roughness, confirming results from the Buckinghamshire pilot.

Additionally, a single track recorded on the same day on the intersection between SP18 and SP19 has been analyzed in further detail. Figure 3 shows all raw collected data gathered by SRS as colored points (from green to red tones). The track contains a short and deteriorated road section (between the blue and light blue dots) and a pothole (white dot). These dots were manually marked as ‘events’ in the inspection track by the road technician, annotated with pictures from the on-board camera. Road quality measurements for the same track are also shown in Figure 4: orange dots indicate the raw data points (they are not equidistant since they were recorded by multiple SRS data collection sessions). The red and blue bars show the beginning and the end of the degraded section of road, as indicated by the visual inspection report, while the grey bar indicates the pothole (an interval of 5 meters before and after is grayed out in the plot). Dashed green lines represent the average PPE³ value on all undegraded sections, while the dashed red line represents the average PPE on the degraded section. Degraded road sections and potholes show a noticeable increase in the average PPE value recorded through SRS, also confirming previous results.

Table 3. Analysis of aggregated road roughness values per road section type.

	Non-degraded sections	Degraded sections	Pothole sections
Aggregated points count	952	839	90
Road roughness average	0.087	0.216	0.408
Road roughness standard deviation	0.094	0.207	0.371
Maximum road roughness	0.678	1.805	1.729
Minimum road roughness	0.006	0.011	0.010

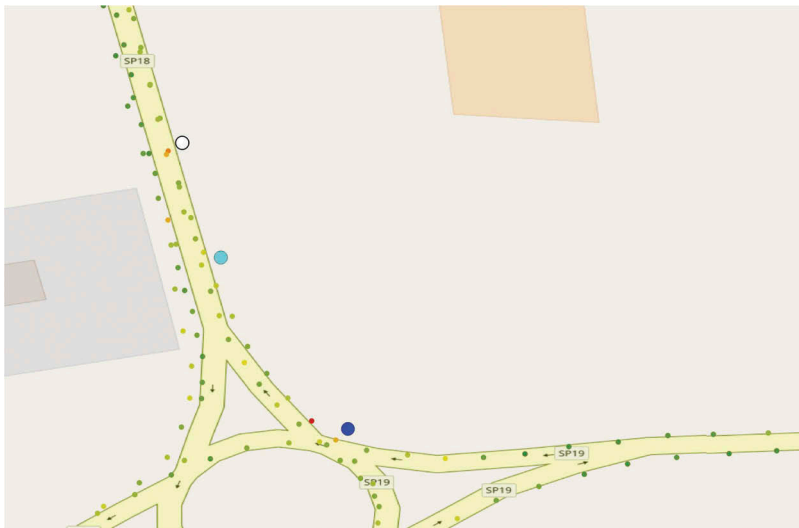


Figure 3. Map of the analyzed track, on the intersection between SP19 and SP18.

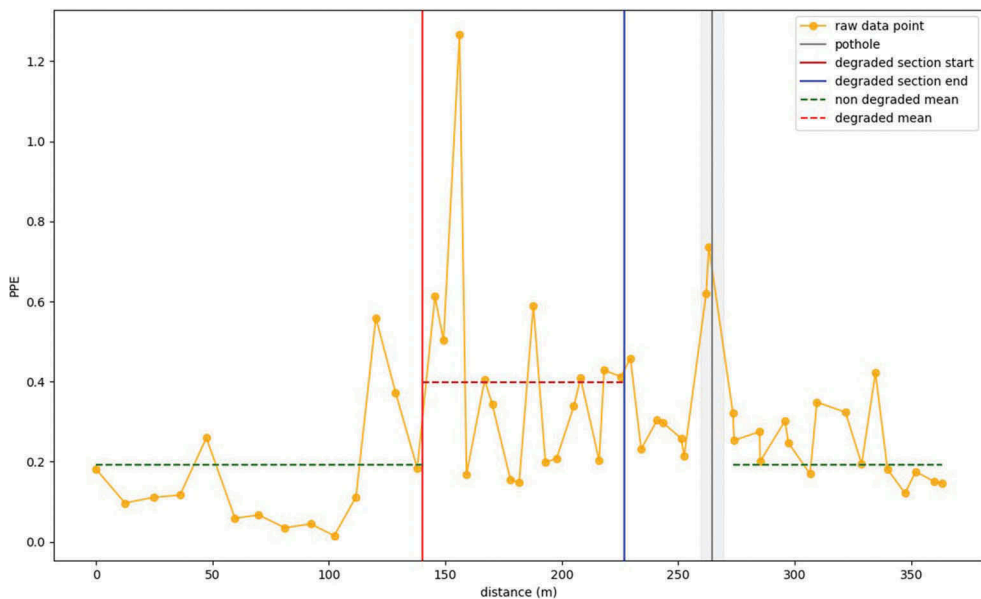


Figure 4. Analysis of collected data on the inspected road section

3.2. Results and comparison to related work

Comparison with visual inspections has shown that not all types of damage to the road are detected with equal reliability. Damage by landslides, depressions in terrain, sloping road surfaces, and imperfections at the lane center are hard to detect using methods adopted by SRS. However, the data validation methods confirm that SRS data is shown to be mostly consistent with manual observations on the field – using authoritative

surveys provided by road technicians – and show promise that collected road quality measurements can be adopted to reliably determine the presence of degraded road sections or surface defects like potholes. When compared with traditional road monitoring techniques, outlined in Section 1.2, SRS is a cost effective and efficient alternative that can be used by large numbers of volunteers without any professional training and any specific equipment, except a consumer-grade smart device.

These results confirm evaluations in literature, attempting to exploit consumer-grade devices to measure standardized road quality measures, such as International Roughness Index (IRI) values. While results are difficult to correlate to standardized measures from professional equipment – even with correction factors depending on speed and type of vehicle – smart devices can be considered a low-cost alternative for real-time pavement monitoring on a large scale (Hanson, Cameron, and Hildebrand 2014). Also, previous studies by Laubis et al. estimated the accuracy of crowd-sensed road monitoring at 85% on average (Laubis, Simko, and Schuller 2016b; Laubis et al. 2018).

Systematic comparison with ground-truth data, statistical quality estimation, and the adoption of user trust and reputation schemes still offer a wide gamut of interesting research challenges aimed at ensuring that collected data is relevant (Restuccia et al. 2017).

4. Discussion

Crowd-based data collection tools allow citizens to participate in the collection of information, a process that can have a substantial value and can be carefully exploited to yield positive economic or social impact. In this context, ‘bottom up’ initiatives drive active citizenship and promote awareness of pain points, needs, and issues affecting local communities and territories, making crowdsensing instrumental in the empowerment and innovation process.

Using mobile crowdsensing systems for road surface quality monitoring can radically change the way agencies handle road maintenance. The systematic coverage of critical road infrastructure can lead to a map of road quality that is updated in near real-time, instead of once a year in periodical surveys or in response to citizen complaints. The road network can be monitored continually, leading to a historical map of the state of infrastructure. Degradation of critical road sections can be monitored closely and, given sufficient historical coverage, predicted to a higher degree of accuracy than with standard methods. As discussed previously, early repairs are critical in ensuring appropriate maintenance operations and preventing further costly reconstructions (European Union Road Federation 2014). Also, accidents due to road damage have a direct economic impact on road operators, in terms of legal fees, damages, and insurance policies, and represent an even greater burden on road users (Islam and Buttlar 2012; Belete-Tekie 2017). Using a tool for low-cost monitoring of the road network, with systematic adoption and active citizen participation, provides an opportunity to drastically reduce these costs.

We suggest that the usage of traditional road monitoring surveys, performed by qualified technicians with special tools and vehicles, be complemented by the adoption of real-time data gathered through public crowd-sensing campaigns. As shown in previous studies, even if crowd-sensed measurements show unavoidable inaccuracies due to the nature of unsupervised data collection, these shortcomings are compensated

by their providing wider coverage and more frequent updates. Integrating these data sources in road maintenance planning and policies can help reduce overall costs for operators (Laubis et al. 2018). These approaches cannot fully replace traditional inspections, but they provide an opportunity of reducing cost and improving the efficiency, repeatability, and reach of monitoring operations (Schnebele et al. 2015).

4.1. Data ownership and privacy issues

Participating in a crowdsensing initiative often requires users to give access to a share of sensitive personal information, among which their location, personal data, and readings from sensors (including microphones). Potential threats to user privacy not only represent a barrier to user participation, but also expose crowdsensing system providers to data ownership and data protection issues (Guo et al. 2015). At least since the introduction of the European General Data Protection Regulation (GDPR) in May 2018, service providers require clear management of sensitive information and direct control by users.

Several examples of privacy preserving techniques and data anonymization mechanisms have been proposed, aimed at defending from common attacks at MCS applications and in ensuring both that users retain control over their data while aggregated data does not disclose private information (He, Chan, and Guizani 2015). Full data anonymization (i.e. the removal of all personal information from collected data) must be weighed against the requirements of keeping user information in order to perform data aggregation or to enable user reputation schemes. Also, the use of certain incentive schemes can hinder data anonymization, particularly for legal reasons when awarding monetary rewards.

Data ownership must also be clearly established, both in what applies to raw data collected by the users and aggregated data processed by the system. In general users are expected to forfeit ownership claims on their data when participating in crowdsensing. It can be argued that users implicitly do so when involved in a rewarding scheme, especially if monetary in nature. However this is not always desirable, nor does it encourage quality or quantity of user contributions.

4.2. Crowdsensing adoption and user rewarding

Crowdsensing initiatives and their data provide useful data only if they are actively supported by many users, contributing with large amounts of data. Data are required both to provide the required coverage and to ensure that aggregated information is reliable (Guo et al. 2015). As shown in the pilot coverage in Table 1, small-scale pilots operating at regional or city-level, where SRS was adopted systematically by regional entities or public transport companies, exhibit a sufficient coverage and a very high redundancy (reaching an average of 30 measurements per aggregated point for the Mantova pilot). In contrast, large areas where usage of the system is not pervasive show far fewer data contributions (often from single users only).

In pure crowd-based scenarios, where data contributions are provided by volunteers freely adopting the system out of good will or personal interest, the applicability of crowdsensing for road quality is strongly limited by the lack of direct incentives. Participation entails a certain

amount of costs and risks for users: mobile devices, when collecting data, deplete scarce resources such as computational power, bandwidth, and energy; collected data may contain sensitive personal information, such as the user's location; and data collection usually requires constant or periodic active intervention by the user. Users require sufficient motivation to overcome these deterrents (Zhang et al. 2016).

Contributions to the generation of a public database of road quality, as discussed above, may help in shortening response times for road technicians and in providing a better infrastructure for road users. This provides an incentive for drivers to participate in the data collection process, albeit indirectly, since road users bear the larger part of costs when driving on degraded road sections (De Weille 1966; Zaniewski et al. 1982). Also, theoretical studies suggest that when encountering roads in very bad conditions, road roughness datasets might be used by navigation software to dynamically reroute to better road quality. In some scenarios, savings in terms of reduced vehicle operating costs may compensate the expenses due to longer travel distances (Laubis, Simko, and Schuller 2016a).

Other, more direct, incentives widely adopted in crowdsensing are of monetary nature, whereby users are compensated for their efforts through credits, vouchers, or fiat money. *Worth One Minute* (WOM), a novel general-purpose rewarding system is currently being developed, aiming at providing crowdsensing and public good initiatives with the required tools to motivate users. WOM is a voucher-based rewards platform whereby public good initiatives can generate vouchers in exchange for work performed by their users. Each voucher is geolocalized and timestamped, effectively representing 'one minute' of time purposefully invested by the user. Participating service and goods providers, including public entities, can then exchange vouchers for prizes, discounts, or any other form of compensation. Vouchers can be filtered by location, time, and type of work performed, thus allowing compensation to be focused towards a specific goal or area. The WOM platform is designed to be completely anonymous and to provide a shared platform for multiple crowd-based initiatives and public operators wanting to promote public good and civic efforts (Klopfenstein et al. 2018a), thus leveraging network effects both on the side of public good initiatives and on the side of reward providers, exploiting the mechanics of platform economics (Parker, Van Alstyne, and Choudary 2016).

From the results presented in Section 3, it is however clear that the most effective solution is provided by the systematic approach: the adoption of crowdsensing systems by public or private entities ensures that users require no further incentives to adopt the system, which instead is used methodically, in a controlled environment, with known equipment, and with a final data coverage that can be finely controlled.

Notes

1. Reference road survey costs in Italy, 2019. Provided by ACI (Automobile Club d'Italia).
2. Official Web site: <http://www.c4rs.eu>.
3. Dimensionless units of 'power of prediction error', used by SmartRoadSense to indicate the roughness of roads through its signal processing model.

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ORCID

Lorenz Cuno Klopfenstein  <http://orcid.org/0000-0003-0380-4824>

Saverio Delpriori  <http://orcid.org/0000-0002-1619-6744>

Alessandro Bogliolo  <http://orcid.org/0000-0001-6666-3315>

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