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RESEARCH PAPER

Enabling crowdsensing-based road condition monitoring service by intermediary

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Abstract

Constant monitoring of road conditions would be beneficial for road authorities as well as road users. However, this is currently not possible due to limited resources. This is because road condition monitoring is carried out by engineering companies using limited resources such as specialized vehicles and trained personnel. The ubiquity of smart devices carried by drivers, such as smartphones and the ever-increasing number of sensors installed in modern vehicles, makes it possible to provide information about the condition of the road on which the vehicle is driving. We develop a smart, crowd-based road condition monitoring service that establishes an intermediary between the crowd as data provider and the road authorities and road users as service customers. In addition to providing customers with accurate and frequent road condition information, subscribers can monetize their collected data. We prove the feasibility and usability of this smart service through analytical and descriptive evaluations.

Keywords Crowdsensing · Internet of things · Road condition monitoring · Multi-sourcing · Service integration · Hotspot analysis

JEL Classification C8 · C13 · C32 · H54 · L86

Introduction

The continuous monitoring of road conditions is crucial for the safety and comfort of road users and for the efficient maintenance of the road network. Road condition information—such as longitudinal and lateral roughness, friction, cracking, surface substance, etc.—is collected by engineering companies using specialized vehicles equipped with high-precision laser, camera, acceleration and positioning sensors. These vehicles and the additional technical personnel required are scarce resources. Thus, the road network is monitored at long intervals or even left unmonitored. In the case of the German federal road network, the road segments are monitored at rather coarse-granular four-year intervals. For country and district roads, there are no common road monitoring rules. This coarse granularity in the temporal dimension limits the utility of current road condition monitoring services. Two examples are mentioned here. The lack of detailed road condition information in the period between two inspections limits the road authorities' ability to determine efficient road maintenance strategies and road users are not able to benefit from real-time warnings about road anomalies.

The wide-spread adoption of smart devices—such as smart phones, smart watches, mobile navigation systems, etc.—and the ever-increasing number of sensors in modern vehicles allow for the supplement or supersession of traditional road monitoring by a crowdsensing-based approach (Eriksson et al. 2008; Mohan et al. 2008; Bhoraskar et al. 2012; Chen et al. 2013; Dennis et al. 2014;

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Laubis et al. 2016b; Wang et al. 2016; Masino et al. 2017). Since the road users are traversing the roads frequently, a nearly real-time and nationwide coverage becomes possible. It can be observed that these crowdsensing approaches have already gained a measure of acceptance within the industry (Forslöf and Jones 2015; Yagi 2014).

However, an unsolved challenge in applying a crowdsensing approach is that a single participant cannot utilize the collected data by selling it directly to road authorities or other road users. This is due to different reasons. First, the raw sensor data does not provide direct insights into the road's characteristics such as roughness, cracks, etc. These characteristics must be estimated based on sensors in commodity devices. Thus, the reliability of the information is lower compared to the information provided by engineering companies. Second, the data that a single participant can contribute is limited in space and time. Such limited datasets are not of interest to road authorities and road users, who require a holistic view of their road network or at least of a freely determinable subset of the network.

On the one hand, there is the huge potential of deriving road condition information from the crowd, whose participants are not able to market this data, and on the other hand, there are the road authorities and road users, who require accurate and frequent road condition information. This results in the need for a new intermediary, able to integrate existing data sources for the purpose of providing a customizable decision support service, what we call a *smart, crowd-based road condition monitoring service*. Since this work builds on a former study of ours, we additionally describe parts of the employed crowdsensing-based road condition estimation methodology for comprehensibility and self-containing reasons (Laubis et al. 2017).

The remainder of this article is as follows: first, the applied research design is presented. Second, a problem definition is provided and requirements for a solution are derived. Thereafter, the knowledge base upon which our artifact is based is discussed. In "Design of the artifact" the artifact, namely the smart service for road condition monitoring, is presented. An evaluation of the artifact is given in "Artifact evaluation". The article concludes by summarizing the contribution to the knowledge base, identifying limitations and providing an outlook on future research.

Research design

For addressing this research question, we apply a design science approach (Hevner et al. 2004). In accordance with the seven design science guidelines, we design a smart, crowd-based road condition monitoring service as an *innovative artifact* and model it as a service map. By considering a new intermediary, it solves the *problem* of bringing together the crowd as a provider of raw data and the road authorities and road users as customers requiring customized road condition information. The artifact *contributes to research* in the domain of service science and crowdsensing. The service map artifact is *evaluated* by instantiating for illustrative purposes the services provided by the new intermediary. The instantiated services are crowd-based road condition estimation as a prediction service and hotspot analysis of road condition information as a decision support service.

We follow the design science research methodology (DSRM) of Peffers et al. (2007). In this section, we provide an overview of which methods we apply and what the results are in each step of the DSRM process model. The problem is identified through discussions with decision-makers from municipal and federal road authorities and with managers from the automotive industry. The knowledge base is reviewed and the identified importance of the problem is discussed with experts from the IS discipline. Thus, a justified problem statement relevant to both the scientific knowledge base and practitioners is derived. The solution to the identified problem is to overcome the difference between the goal state and the current state. Therefore, we identify both the current and the ideal state of a road condition monitoring service. Comparing both, we define concrete requirements in terms of the accuracy and granularity that the target service should fulfill. Metrics are set to quantify the target artifact's ability to meet these requirements. According to the defined objectives of the solution, we design a smart service for road condition monitoring. This artifact is different from current solutions as it considers a new intermediary between the information providers and the information recipients. Hereby, crowd-sensed road condition information can be utilized and thus, the defined objectives of the solution are addressed. The artifact and its components are described as a service map. For iterative improvements of the artifact, intermediary proofs of concept are regularly built and demonstrated to experts from the IS discipline and from the road maintenance and automotive domains. This results in a proof-of-concept-validated artifact in a naturalistic setting for formative reasons. For summative evaluations, we choose analytical methods to determine the degree to which the artifact fulfills the specified requirements given a certain scenario. More precisely, for rigorously demonstrating the quality and applicability of the artifact, we perform analyzes regarding the specified metrics. Hereby, we show the accuracy and functionality of the artifact. Encouraged by these findings, we also evaluate the artifact's value to road authorities in the more specific scenario of scheduling road maintenance actions. We perform a descriptive evaluation by considering additional information from the knowledge base from which to draw informed arguments, demonstrating the artifact's utility within this scenario. This results in an analytically and descriptively evaluated artifact. The problem, its importance and our analysis of the designed artifact as a solution are of presumed interest to IS researchers and are herewith published in a peer-reviewed academic journal.

Problem specification

There are two main stakeholders of road condition information: road authorities responsible for maintaining the road network and road users, who benefit from good road conditions. In this section, the role and needs of these two groups, which are currently unmet by road condition information services, are described for the purpose of deriving requirements regarding the design artifact.

Road authorities require road condition information for maintaining the road network asset. Data collection drives are usually performed during summer-time. Afterwards, the raw data is analyzed and maintenance tasks are scheduled. However, these tasks are performed in spring at the earliest. It is neither possible to efficiently schedule maintenance tasks on up-to-date information nor to react to unexpected damage or deterioration which require instant repairs. From a road authority's perspective, this results in a great need for road condition information in a more frequent and timely manner. It is essential for efficient maintenance planning that the information regarding road condition stays reliable.

Road users are another group that has an interest in road condition information. Road users themselves can make use of knowing about the condition of the road ahead. Laubis et al. (2016a) investigated the savings potential of drivers relying on a navigation system that not only considers the distance traveled and the amount of traffic for estimating arrival time and costs, but also the road condition of the chosen route. Especially for regions with roads in particularly rough condition, they found that there is a substantial potential to reduce vehicles' wear, fuel consumption and travel time costs by rerouting to smoother roads. The immediate and reliable determination of road conditions would also allow for the anticipation of hazardous situations caused by bad road conditions. However, current monitoring services are incapable of providing frequent data and are difficult to access for road users.

For both stakeholders, we identify the common need of having road condition information more frequently available subject to the condition that the information is reliable. The objective of the new artifact is to contribute to filling the gap between the target state of having reliable, real-time information and the current state of performing expensive inspections at relatively large time intervals. Accordingly, we address the following research question: *How can a smart road condition monitoring service make use of crowd-sensed information for serving the needs of both stakeholders: road authorities and road users?*

The design artifact is intended to provide an answer to this research question. To rigorously determine the utility of the design artifact, we derive two metrics for evaluation: For evaluating the reliability of the provided information, we deploy the *coefficient of determination* R^2. It describes the proportion of variance that can be explained by the artifact's inspections compared to the variance of current high-quality inspections. Thus, it is a feasible measure for providing information about the goodness of fit of the inspections. For evaluating the ability to provide meaningful road condition information on a frequent basis, the artifact should be able to determine relevant areas not only in a spatial but also timely, fine-grained manner. Therefore, we assume the *ability to determine significant spatio-temporal hotspots* (for example, on a monthly basis) as a suitable criterion by which to evaluate the artifact's utility to the stakeholders.

Knowledge base

Road infrastructure monitoring is a service system in which road users, road authorities and service providers interact and mutually create value. Road authorities require service providers to monitor the road condition. They provide the service of an adequate and safe road infrastructure to taxpayers, the road users. Service providers—for example, engineering companies—only create value if the infrastructure is utilized by the road users. Maglio et al. (2009) identify this "co-creation of value" by "a configuration of people, technologies [and] organizations" in the system as a primary characteristic of service systems. In road condition monitoring, however, the road users, as an integral part of the service system, neither participate in the road condition monitoring nor have access to up-to-date road condition information.

Barile and Polese (2010) define smart service systems as systems that are designed for self-management and self-reconfiguration to ensure the provision of a satisfactory service to the participants. As they raise participants' service satisfaction, service systems, including smart services, are being introduced in various domains such as electricity grids, home automation and smart city architectures (Farhangi 2010; Anttiroiko et al. 2014; Byun and Park 2011). Allmendinger and Lombreglia (2005) argue that a key element of smart services is the introduction of intelligence into the service landscape, which facilitates higher customer engagement with existing services and enables new services. In today's system, communication between road users and road authorities is difficult and customer engagement is low.

Consequently, the service system of road condition monitoring exhibits deficiencies with regard to the satisfaction of road users' and road authorities' needs.

In order to provide a smart service for road authorities and road users, road users have to be integrated into the monitoring process. As this requires multiple service providers as sources of road condition information, multi-sourcing service integration was found to be relevant. Multi-sourcing service integration covers different management approaches and business processes by which to integrate various external service providers and their interdependent services into an existing organization (Goldberg et al. 2014). Research on multi-sourcing integration originates from the domain of IT outsourcing and has experienced a rise in scientific interest in recent years, as multi-sourcing strategies become increasingly important for companies (Herz et al. 2010; Bapna et al. 2010). Originally, the retained organization, meaning the part of the IT that is kept in-house and is not outsourced, integrates the services of multiple service providers (Dibbern et al. 2004; Goldberg et al. 2014). As the integration of crowd-sensed road condition information requires complex analytical processing, road authorities lack the ability to integrate all relevant data sources. Therefore, this integration model is not applicable in our case. A different integration model for road condition monitoring service providers is necessary.

Unterharnscheidt and Kieninger (2010) identify the management of multiple providers as a challenge for companies seeking to adapt a multi-sourcing service strategy. In the case of interdependent services, management of multiple service providers is difficult (Goldberg et al. 2015). Gallivan and Oh (1999) classify outsourcing relationships in a service network. According to the authors' taxonomy, road condition monitoring can be classified as a complex outsourcing relationship because multiple service providers (various engineering companies with the ability to produce accurate measurement abilities) can provide their service to multiple customers (road authorities and road users). Making the crowd part of the system, this relationship becomes even more complex as a great number of new service providers with different levels of quality enter the market. This underlines the necessity for a separate role of service integrator in the domain of road condition monitoring, especially for the alignment of different service quality levels.

Rajamäki and Vuorinen (2013) provide a framework for multi-sourcing service provider management. Existing methods are adapted and applied to multi-sourcing service management in public protection and disaster relief organizations. However, they describe a higher-level framework and cover a different domain, which is why their findings are not applicable in our case.

Goldberg et al. (2014) identify five concepts of managing the integration of multiple service providers in a service network. In addition to the traditional concept of integration in the retained organization, the role of integrator can also be fulfilled by a prime provider (one of the service providers), which can be a separate integration entity, or the responsibility can be distributed between the stakeholders in the value network. The concepts of a prime provider and a separate integration entity are both applicable to the case of road condition monitoring, as they take the task of complex data processing away from road authorities. However, the authors provide a generic framework for multi-sourcing service integration, whereas we focus on providing a framework specifically applicable to the domain of road condition monitoring. Since providing a smart road condition information service is essential for road authorities and road users, and has not yet been addressed in research, this work introduces a general framework for a smart service integrating road condition information from various sources.

Design of the artifact

Figure 1 outlines the smart crowd-based road condition monitoring service and the services it comprises.

The model is based on the concept of service maps, which are adapted to the specific requirements of road condition monitoring. A service map is a visualization of relationships between services and the involvement of stakeholders in these services. In the following section, the status quo in road condition monitoring and the change brought about through the introduction of a new intermediary are explained based on the concept of service maps.

Service map

The individual services are visualized as small rectangles that are assigned to service layers. Based on the service typology developed by Kohlmann et al. (2010), we divide our model into four service layers. The data and analysis service layers represent technical services. The separation into data and analysis services was introduced by Demirkan and Delen (2013). Additionally, we divide business services into regular business services and smart services to emphasize the need for an intermediary to integrate the crowd into the market and provide customer-centered services. *Data services* are basic data collection services in our model. They do not provide any value to a potential customer by themselves. They can be differentiated according to the data source, the data frequency and the data quality. *Analysis services* encompass data processing services needed to derive meaningful information from raw data and to draw conclusions based on the derived information. Analysis services are the foundation for business services as only processed raw data provides value to potential

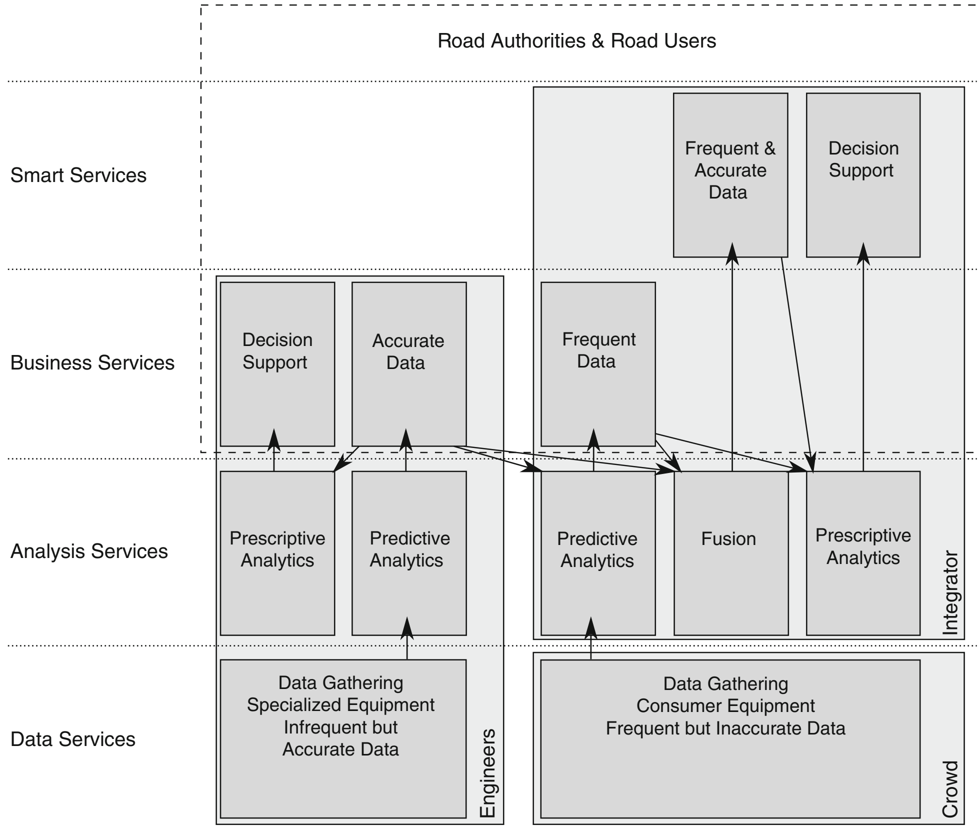


Fig. 1 Service map of smart, crowd-based road condition monitoring service enabled by new intermediary integrating multiple data sources

customers. *Business services* represent services that are of value to certain customers and thus can be marketed to them. *Smart services* are services that combine business services or other smart services to derive additional information and offer new services. This layer bears similarity to the *service cluster* layer as described by Kohlmann et al. (2010) in that it uses the outcome of underlying business services. Yet, in contrast to a service cluster, the outcome of existing business services is not only clustered, but first redirected to the analysis layer, where further analytical steps provide the information that is the basis for the resulting smart service. In addition, it is a necessary condition for a smart service in the crowdsensing-based road monitoring domain to be enabled by a fusion of data from engineering companies and the crowd. Thus, a smart service meets the different demands of customers regarding space, time and accuracy of road condition information. Smart services also differ from business services in that they integrate single business services and provide an automatic tailoring to the customer's needs. The frequent data service, however, remains a business service, as accurate data from engineering companies is required for the calibration of crowd measurements, although this accurate data itself is not included in the services offered to the customer.

Only the two upper layers, namely business services and smart services, can be used by the two stakeholders *road authorities* and *road users*. This is indicated in Fig. 1 by the dashed rectangle. Subsequent to assigning the services to service layers, we group the services according to the type of actor who provides them. Relevant actors are the *engineering companies*, the *crowd* and the new intermediary, called the *service integrator*. This grouping is indicated by rectangles surrounding the individual services. Services depend on each other. A service may require the output of one or more other services. This is indicated by arrows. The arrow is directed from the supplying service to the consuming service. These dependencies can cross layers and can exist within the boundaries of one type of service provider or they can exist between different types of service providers.

Current situation

Nowadays, if a standardized and technology-based road condition monitoring approach is applied at all, it is mainly based on *gathering raw data* with special purpose vehicles and specially trained persons. Data gathering is conducted by engineering companies. The collected raw data—such as GPS-based coordinates, laser-measured road profiles, vibration patterns, high-resolution images, etc.—are of high quality due to the specialized and sound calibrated sensors. This data gathering service is located in the bottom layer of the service map and is connected to the *predictive analytics* *service*. The predictive analytics service includes all tasks that relate to using the raw sensor data to derive information and metrics that are meaningful for road authorities and road users. For example, after one has taken equidistantly spread vertical laser sensor readings from a moving vehicle, a continuous longitudinal profile must be derived from these readings. Given this road profile, a single roughness metric that integrates different frequency bands of the profile may be calculated. A prominent roughness metric is the international roughness index (IRI). The IRI was defined by a multinational research consortium in 1986, which was funded by the World Bank (Sayers et al. 1986). The IRI developed into a quasi-standard for describing longitudinal road roughness conditions and is monitored as a key metric by most road authorities nowadays. Such metrics are meaningful for road authorities, since they provide insights about the actual value of their road network asset. Furthermore, such information is considered when allocating budgets for maintenance tasks. In addition to road authorities, information concerning the current road condition is of interest to road users, as well. They benefit from the fact that, for example, they receive information about the condition of the road and can thus adjust their driving behavior accordingly. Since this information is meaningful for road authorities and road users, the data can be provisioned to them directly. Thus, the *accurate data provisioning service* of engineering companies is a business service and accordingly located in the service map. Considering that the customers have to come up with decisions based on this accurate data, prescriptive analytics tasks must be performed subsequently. Road authorities have to decide when to perform which maintenance action at which road section, and road users have to decide whether to take a detor based on rough road conditions ahead. The application of such *prescriptive analysis services* by the engineering company allows for the provision of *decision support services* with direct managerial implications to the two main customers, road authorities and road users. As previously mentioned, these services rely on highly accurate sensor readings, but the relatively high costs and scarcity of resources prohibit frequent measurements. Thus, the business services provided by the engineering companies are accurate and reliable, but of low frequency.

Extension by new intermediary

The tasks of the new intermediary, as an enabler of a smart, crowd-based road condition monitoring service, are to manage the demand of the customers, namely the road authorities and road users, and to integrate new and existing crowd-based data suppliers in order to serve these demands.

The current approach of performing road condition monitoring without a service integrator does not allow the crowd to market their data. This is indicated in Fig. 1, which shows that the crowd by itself does not have any services in the business or smart service layer. A single participant gathering inaccurate raw data requires an actor to perform analysis steps in order to make the data valuable for road authorities and other road users. Therefore, the intermediary has to come up with a payment regime reflecting the quality of the data provided by the individual service suppliers. Given this service integration model, road users, who contribute by sensing the road's condition, directly benefit by being compensated for the data they contribute. This is possible only because the service integrator can aggregate the amount of participants necessary for making the crowd-sensed information sufficiently robust and reliable. As with the engineering companies, meaningful road condition metrics have to be derived from this raw data. This can be achieved by applying supervised machine learning algorithms to the raw data for calibration, which is represented by the *predictive analytics service* of the integrator. However, these supervised algorithms require information on the actual road condition for training purposes. Thus, the integrator has to commission accurate road condition measurements for calibration. The integrator has to decide when and for which road segments a procurement of the accurate ground truth is beneficial. For this reason, it is necessary to consider when and where a calibration of new participants is required. Furthermore, the procurement of accurate data is necessary for road segments on which participants with inaccurate models drive. These participants require a model recalibration, which is necessary, for example, because of changes in the car, the sensors, the driving behavior, etc.

This should be done to enable the efficient and smooth integration of new participants and an easy recalibration for already-existing participants. Such a self-calibration approach is described by Laubis et al. (2016b). Even though combining multiple crowd-based road condition measurements leads to a more robust road condition prediction, the provided data tends to be less accurate. However, in this way the integrator can provide a *frequent data service* to road authorities and road users. The information demand of customers, and especially road authorities, differs depending on the decision that has to be supported. Decisions that require specific information are, for instance, maintenance scheduling, budget planning, estimating the road asset value, technical acceptance of new construction or resurfacing work, driver navigation, and hazard warnings. Furthermore, the service has to be customizable depending on the road network under consideration. It has to be determined whether a nationwide network, a certain city or a single road segment should be inspected. Additionally, the road type, the surface material and the amount of traffic must be taken into account when analyzing and offering the data. For meeting these customization needs, a *fusion* of highly accurate data from engineering companies and more frequent (but less accurate) data from the crowd can be utilized. Thus, in addition to the decision of purchasing ground truth data, the intermediary also has to decide when to purchase and when to perform which service in order to most efficiently meet the demands of customers. Within such an arrangement, the different data sources have to be weighted according to their reliability, i.e. their sensing accuracy and timeliness.

The intermediary can customize the provided service depending on the individual information demands of the customer. In the case of road authority customers, for example, roads that are old and likely to degrade in an unforeseen way require more frequent measurements than roads that are quite new. Likewise, road segments made of concrete should be monitored more frequently on hot summer days, since they tend to suffer from so called "blow ups", which are sudden bucklings of the concrete elements. In contrast, newly constructed or newly paved roads do not require temporally fine-grained monitoring, but a few accurate final inspections for acceptance of the work. Thus, an integrated and customized smart, crowd-based road condition monitoring service based on *frequent and accurate data* becomes possible. In addition to providing the road authorities and road users with customized road condition information, the intermediary is able to provide a *decision support service* by applying *prescriptive analyzes*. Road authorities and road users are most likely to be interested in identifying these road sections that differ significantly from others. In addition, clusters of road segments in poor condition can be of high relevance. Such segments, called hotspots, can reveal essential insights and allow for a prioritization of maintenance tasks. In doing so, one must also consider which level of accuracy and timeliness of the data is required by the customer.

Artifact evaluation

We follow a twofold approach regarding the evaluation of the artifact. On the one hand, we select analytical methods to determine whether the artifact fulfills the specified requirements of reliability and an increase in the temporal resolution. By performing analytical evaluations, we demonstrate the quality and technical applicability of the artifact. On the other hand, we perform a descriptive evaluation by drawing information from the knowledge base and rigorously evaluating the artifact's value to road authorities in the scenario of scheduling road maintenance actions.

Crowd-based road roughness prediction

For ensuring the reliability, we consider the road profile information from the district road K3535 in Germany with a distance of 2.28 km for each direction. This profile information is provided by the Institute of Highway and Railroad Engineering (ISE) at the Karlsruhe Institute of Technology (KIT). It is measured by special laser-equipped vehicles and can be considered equivalent to the data provided by an engineering company. We calculate the IRI for 100 m segments with an overlap of 80 m. This results in 220 samples amounting to 4.56 km overall. These values are used as ground truth for training a prediction model.

For generating crowd-sensed data for the analysis, we perform seven test drives with a passenger car that is equipped with an Android-based Nexus 4 smartphone. The smartphone is placed in the middle of the dashboard and fixed with a car mount. For each drive, the smartphone is used for recording the GPS coordinates, as well as the accelerometer and gyroscope sensor readings. A new GPS fix is determined nearly every second and the frequencies at which the accelerometer and gyroscope sensors are recorded hover around 50 Hz, with slight variations. The speed is kept at a constant of around 75 km/h for all drives. The test drives and the measurements from the laser profiler are taken separately and the passenger car is not equipped with additional sensors. Thus, the car can be regarded as a new participant in a crowdsensing-based monitoring system.

A map-matching to the road network, common to all seven drives and to the laser-measured IRI, is used to align measurements from multiple drives and the actual road condition. From the accelerometer sensor, we consider the absolute readings as well as the relative linear acceleration—excluding the gravity. The raw data stream of each sensor is aggregated by 100 m road segments. The reason for choosing 100 m segments is because most official road condition monitoring systems also consider this segment size. Since the road's waviness can be described in terms of frequencies, we also perform a continuous wavelet transformation on the accelerometer and gyroscope readings for extracting features reflecting the frequency content (Torrence and Compo 1998). This results in a total of 95 features, which are all z-score normalized.

A random forest regression model is built for each drive separately, with the actual IRI as the outcome variable (Breiman 2001). We choose random forests since in our former study they outperformed other methods such as support vector machines (Schölkopf 2006). The overall dataset is split into 80% training data and 20% test data. Here, care is taken to ensure that the segments in the training set do not overlap geographically with those in the test set. In addition to this overall data splitting, each model is cross validated and tuned by the number of randomly chosen features for each tree to address overfitting. The metric considered for cross validation is the coefficient of determination R^2 as a metric representing the goodness of fit of the predictions.

The single prediction models are tested on the remaining out-of-sample test set. The performance of each model is determined by the goodness of fit metric R^2 and is presented in Table 1.

The R^2 indicates how much of the variance in the ground truth data is explained by the prediction model. It is a widely used metric for determining the goodness of fit of a model and thus its reliability. Since it is a relative measure, it is easy to interpret and more easily comparable among models than, for example, absolute error metrics. It is shown that single cars can contribute to a crowdsensing-based road roughness monitoring system with a mean R^2 of 67.83%. For the considered seven drives, the R^2 ranges from 59.68% to 76.79%. This degree of determination can be considered as relatively reliable.

Frequent decision support by hotspot analysis

For a second analytical evaluation to determine whether frequent decision support can be provided, a hotspot analysis is applied to a crowd-sensed road condition dataset obtained from BumpRecorder and covering the geographical region of Aizuwakamatsu in Japan (Yagi 2014). The data is collected using smartphone accelerometer sensors, which are attached to the dashboard of the car. The dataset contains already-derived IRI values processed through predictive analytics, which is in accordance with our approach as described in the previous section. Even though the process applied for the IRI calculation is the intellectual property of BumpRecorder, it can be expected to be similar to ours. The dataset is chosen due to the fact that it covers a large region and includes multiple data suppliers. It also covers several months of the year 2016, which allows for an investigation of the temporal evolution of hotspots.

Table 1 Out-of-sample performance of crowd-based IRI predictions

Drive	R^2
1st drive	0.6319
2nd drive	0.5968
3rd drive	0.6207
4th drive	0.7395
5th drive	0.7679
6th drive	0.7115
7th drive	0.6799
Max	0.7679
Mean	0.6783
Min	0.5968

We preprocess the data by assigning each individual measurement to a cell of a spatial grid with an edge length of 22 meters. A measured instance is characterized by longitude and latitude coordinates and the time at which the road condition is measured. According to the temporal dimension, a period from January to October 2016 is covered. The dataset consists of 1,443,632 measurements. On average, 2.35 instances per grid cell are measured each week. The most frequented roads (third quartile of aggregated instances per cell) are measured 4.68 times a week.

Hotspot analysis is a tool for determining patterns of spatial or spatio-temporal autocorrelation in a geographical area (O'Sullivan and Unwin 2002). It can be used for providing decision support. Thus, it is regularly applied in various fields such as criminology, epidemiology, traffic safety, etc. (Ratcliffe et al. 2011; Goovaerts and Jacquez 2005; Sugumaran et al. 2009; Steenberghen et al. 2004). Hotspots provide a robust insight into the local environment of a measured instance. Regarding the domain of road condition monitoring, a hotspot can be defined as a geographical cluster showing a concentration of bad road conditions. Providing a hotspot analysis as a smart service enables road authorities to focus their maintenance activities on the most relevant areas. This provides additional decision support to the customer, since no further data analysis is required. Different statistical metrics can be applied for the purpose of revealing hotspots. We choose the Getis Ord G_i^* metric, as it enables the detection of spatial associations of a geographical region with adjacent regions within a selected distance d. Additionally, G_i^* measures are z-score normalized. This inherently allows for the determination of statistically significant hotspots (Ord and Getis 1995). Other applicable metrics are Local Geary's C and Local Moran's I (Anselin 1995). The latter is especially suited to detecting local outliers such as potholes. The G_i^* statistic is defined by Eq. 1.

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} \cdot x_j - \bar{X} \cdot \sum_{j=1}^{n} w_{i,j}}{S \cdot \sqrt{\frac{n \cdot \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2}{n-1}}} \tag{1}$$

S is defined by Eq. 2.

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \bar{X}^2} \tag{2}$$

The elements $w_{i,j}$ of the spatial weight matrix W are defined according to Eq. 3.

$$w_{i,j} = \begin{cases} f(d_{i,j}) & , \forall \quad d_{i,j} \le d \\ 0 & , \text{else} \end{cases} \tag{3}$$

G_i^* is calculated for every cell i in the spatial grid considering the IRI value x_i of the cell itself and the values x_j of adjacent cells within the convolution distance d. The adjacent cells contribute to G_i^* depending on the spatial weight $w_{i,j}$ that is attributed according to their distances $d_{i,j}$ to cell i. Thus, the x_j of a close adjacent cell can have a stronger influence because of a higher spatial weight $w_{i,j}$ than that of an adjacent cell that is located farther away. The cell's deviation from the expected value is determined and standardized to provide the z-score.

The hotspot analysis is an instance of a prescriptive analytics service, which is the basis of a decision support service, a smart service in our model. It can be customized to the specific needs of a single stakeholder depending on the parameterization of the G_i^* statistic. The weight matrix W and the convolution distance d can be modified according to the customers' needs. Furthermore, the contiguity definition can be altered to Chebyshev distance ($d_{i,j} = \max\{\|r_i^{(1)} - r_j^{(1)}\|, \|r_i^{(2)} - r_j^{(2)}\|\}$, with $r_l^{(k)}$ depicting the spatial grid coordinates of the regarded cells) and Manhattan distance ($d = \|r_i^{(1)} - r_j^{(1)}\| + \|r_i^{(2)} - r_j^{(2)}\|$) for further customization (Cha 2007). Thus, services tailored to different customers can be provided by the intermediary. A road authority in charge of maintaining a highway, for instance, might consider a greater distance d and spatial weights of inverse distance $f(d_{i,j}) = 1/d_{i,j}$ if maintenance actions affect larger road segments. For road authorities that cover the grid of a city and are interested in local anomalies, a smaller distance d and spatial weights of inverse square distance $f(d_{i,j}) = 1/d_{i,j}^2$ would be more appropriate. Road users who want to have a more convenient ride in their cars might even have different requirements regarding the setup of the hotspot analysis. The new intermediary can provide this flexibility by offering an individualized service to each customer.

We aggregate the road condition data over the whole timespan and apply a hotspot analysis based on the G_i^* statistic. Here we choose the Manhattan distance to calculate $d_{i,j}$ for adjacent cells and set the convolution distance to $d = 2$. The spatial weights are set to $w_{i,j} = 1/d_{i,j}$ for $i \neq j$ and $w_{i,i} = 2$. Figure 2 provides the resulting map of identified spatial hotspots. Longitudinal and latitudinal coordinates define the geographical location of the hotspots. A light-colored spot indicates a higher G_i^* value and thus a cluster of bad road segments. The number of unique cells in the spatial grid with road condition data available is $N = 69,689$, of which 6,999 cells, or 10.04% of the considered road network, are identified as hotspots at a 95% confidence level. Considering a 99% confidence level, 3,893 cells, which account for 5.59% of the examined road network, are identified as hotspots. Figure 3 provides a more detailed insight into the result by displaying hotspots in the city center of Aizuwakamatsu.

Next, we apply a spatio-temporal hotspot analysis. We aggregate the data on a temporal basis. To do so, we select a monthly level, as it provides sufficient data consistency and measurements. The number of measurements in the examined period is stable. To demonstrate the feasibility of

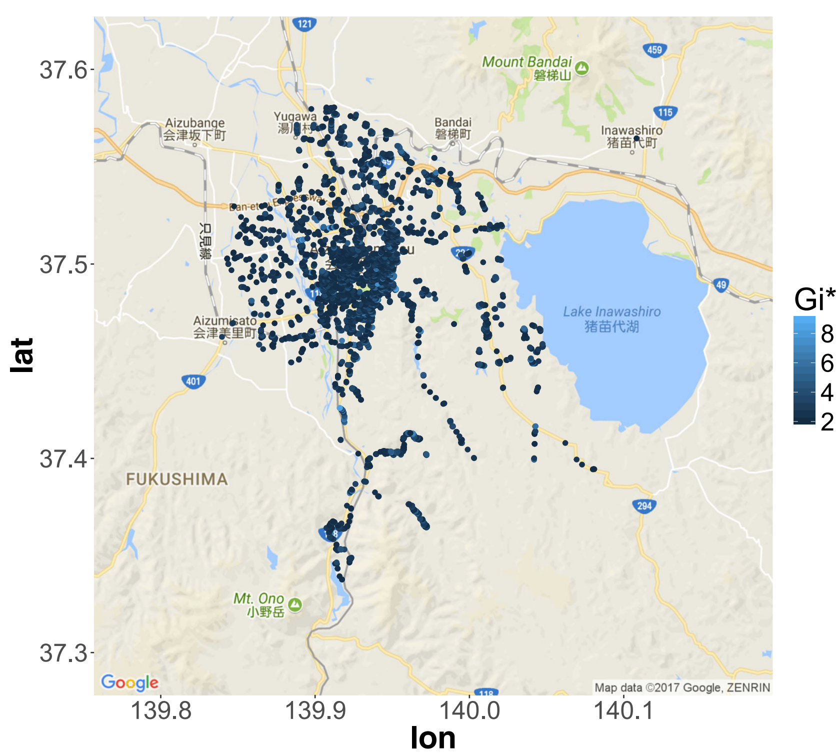
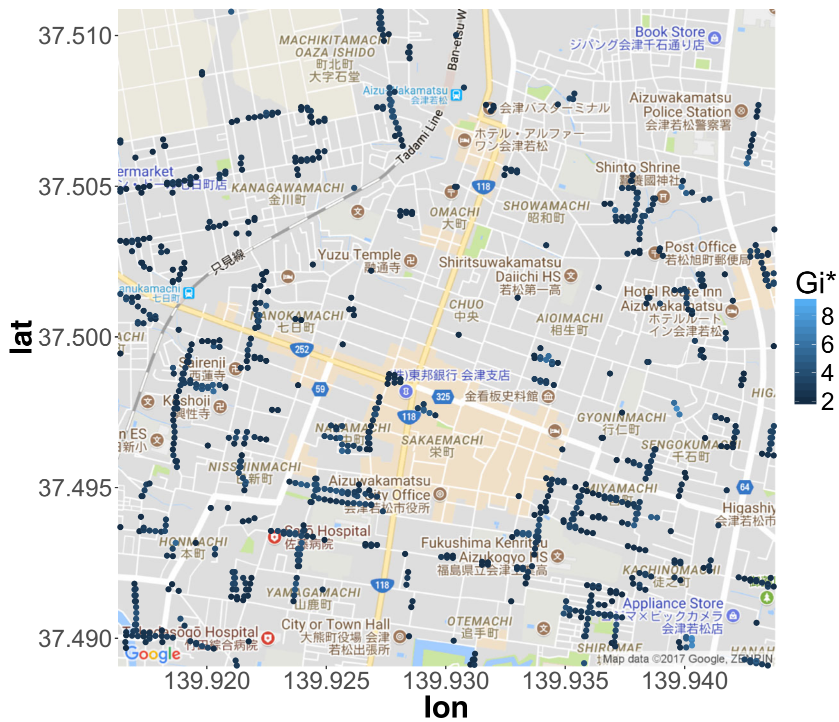


Fig. 2 Spatial distribution of hotspots at a 95% confidence level - region overview

Fig. 3 Spatial distribution of hotspots at a 95% confidence level - Aizuwakamatsu city center



determining changing patterns in the hotspot distribution, three different time periods are analyzed. In a first step, the monthly subsamples are filtered for similar cells in order to produce a consistent data base. Then, identified hotspots are compared between the different time slots. January, May and September of 2016 are selected, as they are equally distributed on a temporal axis. These three subsamples share a quantity of $N = 20,184$ grid cells, which are considered for further analysis. Applying a hotspot analysis, 819 common hotspots are identified, which accounts for 4% of all considered grid cells. The spatial distribution of the collective hotspots over all three time slots is presented in Fig. 4. Hotspots that are exclusively detected in specific time slots are provided in Figs. 5, 6 and 7.

Fig. 4 Spatial distribution of common hotspots

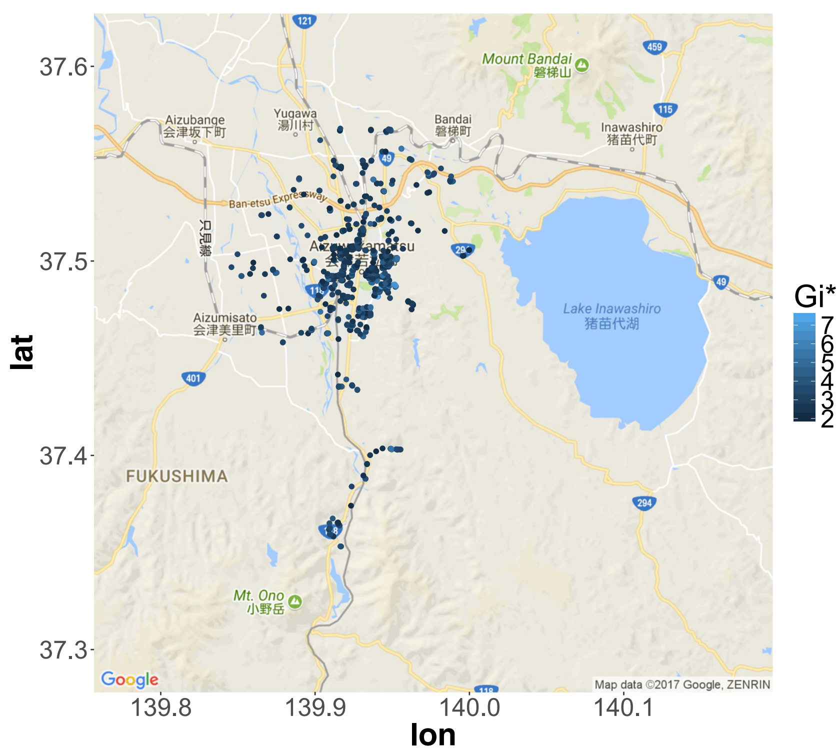
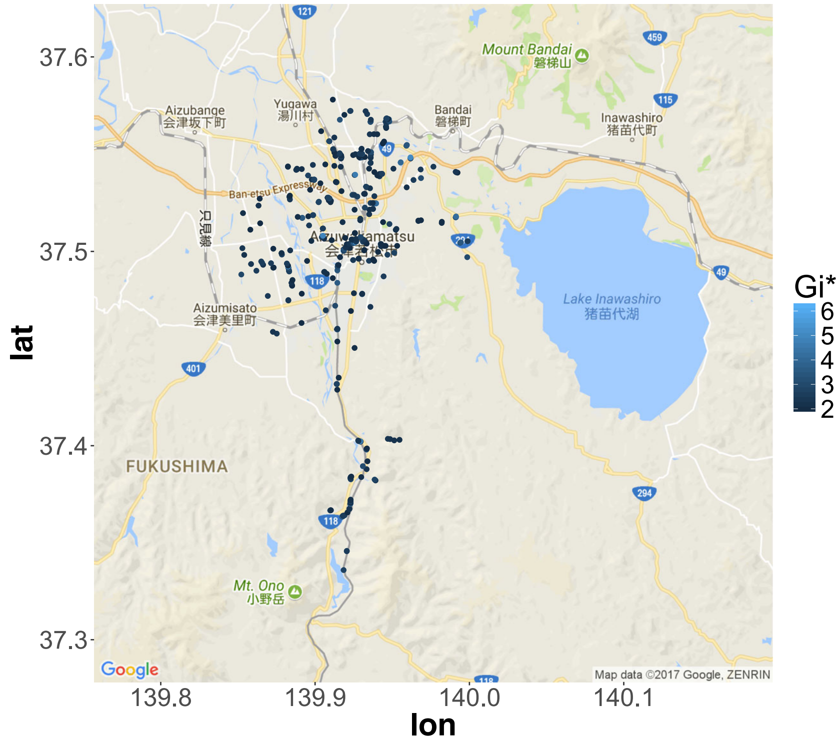
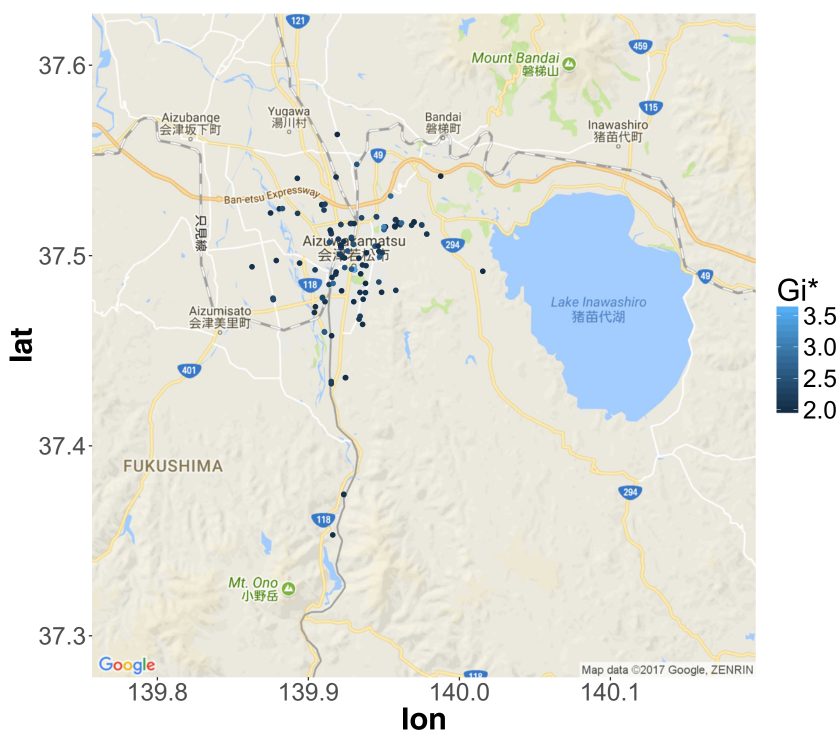


Fig. 5 Spatial distribution of exclusive hotspots 01/2016



It can be observed that in the month of May, the amount of additionally identified hotspots is substantially lower ($N = 131$) than in January ($N = 378$) and September ($N = 378$). Thus, our results show that it is possible to determine changing patterns in road condition on a monthly basis. This fulfills the need of road authorities and users for frequent road condition monitoring. Additionally, with an increased amount of crowd-sensed data, the same method could be applied to provide data concerning hotspots even more frequently, leading to real-time road condition monitoring.

Fig. 6 Spatial distribution of exclusive hotspots 05/2016



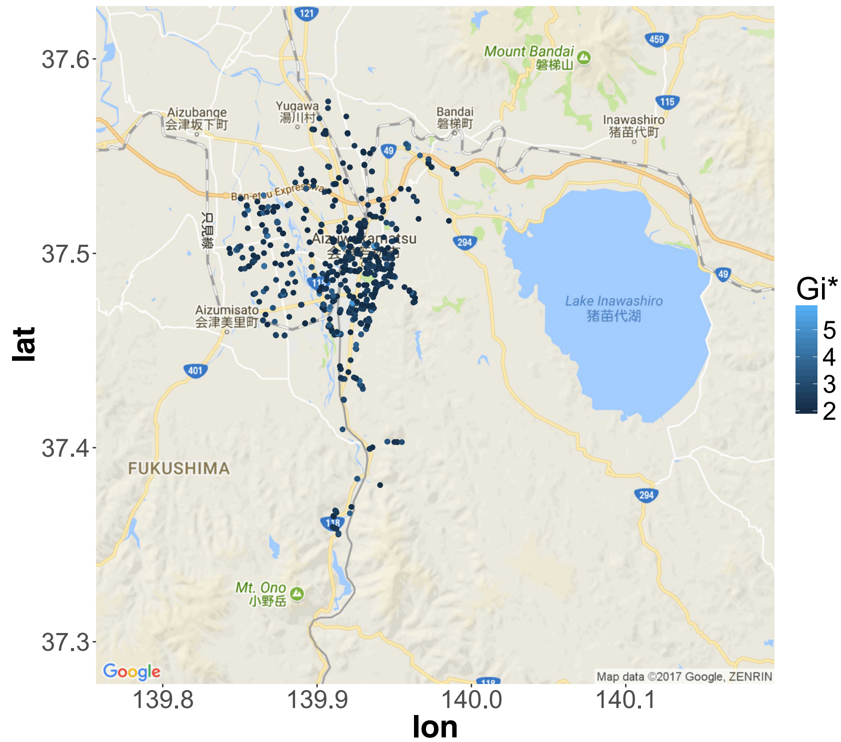


Fig. 7 Spatial distribution of exclusive hotspots 09/2016

For evaluation purposes, we define and calculate a metric describing the timeliness of hotspot detections with different temporal granularities. We can compute hotspots at different temporal granularities—for example, monthly versus yearly. It is obvious that monthly hotspot reports can provide information sooner than those generated on an annual basis, as outlined in Fig. 8a. This can be formally defined as a metric T (timeliness), which allows us to compare two methods that use different time granularities. Let F be a method that uses the finer-grained granularity (in our evaluation, a monthly reporting period). Let C be a method that uses the coarser-grained granularity (in our evaluation, a reporting period of ten months). Each method delivers a tensor of measurements, which has two spatial dimensions and one temporal dimension. We denote a single cell in the tensor F as $F^{(t)}_{x,y}$, where t is the time coordinate and x and y are the space coordinates. In our example, $t \in \{0, -1, \ldots, -9\}$. The tensor from C is a simple matrix since it represents only a single time point. Therefore, we use the notation $C_{x,y}$ for a single cell.

According to Eq. 4, the timeliness metric T is computed as a normalized sum of penalty scores S from all pixels

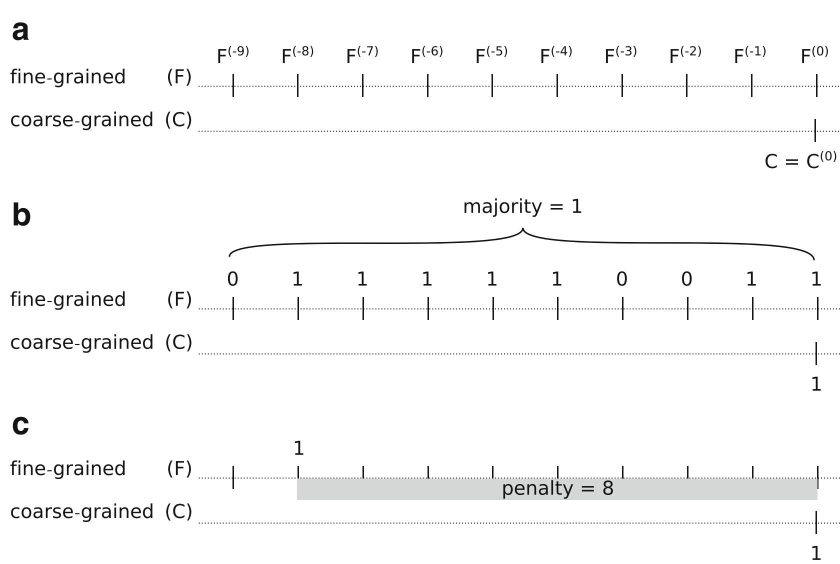


Fig. 8 Overview of the determination of the timeliness metric T based on a comparison between hotspots on temporally fine- and coarse-granular data

where the coarse-grained model agrees with the majority of the fine-grained models.

$$T(C, F^{(0)}, F^{(-1)}, F^{(-2)}, \ldots) = \frac{Score}{Norm} = \frac{\sum_{\forall x,y} S(C_{x,y}, F^{(0)}_{x,y}, F^{(-1)}_{x,y}, F^{(-2)}_{x,y}, \ldots)}{\sum_{\forall x,y} A(C_{x,y}, F^{(0)}_{x,y}, F^{(-1)}_{x,y}, F^{(-2)}_{x,y}, \ldots)} \quad (4)$$

The score S and the agreement factor A for a single pixel are defined by Eqs. 5 and 6, where $m = median(f^{(0)}, f^{(-1)}, f^{(-2)}, \ldots)$ reflects the majority.

$$S(c, f^{(0)}, f^{(-1)}, f^{(-2)}, \ldots) = \begin{cases} \min\{i : f^{(i)} = m\}, & \text{for } c = m \\ 0, & \text{for } c \neq m \end{cases} \quad (5)$$

$$A(c, f^{(0)}, f^{(-1)}, f^{(-2)}, \ldots) = \begin{cases} 1, & \text{for } c = m \\ 0, & \text{for } c \neq m \end{cases} \quad (6)$$

Figure 8a exemplifies fine- and coarse-granular hotspot detections in a temporal comparison. The corresponding determination of the majority m is shown in Fig. 8b. In this example, positive detections are the majority. Figure 8c illustrates the number of fine-granular time intervals by which the coarse-granular detection later detects a hotspot.

In our evaluation, the fine-grained data corresponds to monthly aggregates, and the coarse-grained data corresponds to the aggregation over 10 months. Consequently, the highest score for a pixel, according to Eq. 5, is nine. Applying Eq. 4 to our dataset results in $T = 8.37$. Thus, performing measurements more frequently results in hotspots being detected 8.37 months earlier on average compared to the coarse-granular measurement intervals. Given the fact that the hotspot assessment from coarse- and fine-granular aggregation coincide in 69.3% of all cases, a high consistency of hotspot detection can be claimed with confidence.

Utility to authorities, intermediary and participants

Since the artifact is supposed to be a smart service, the stakeholders and the artifact's utility to them are of inherent importance (Allmendinger and Lombreglia 2005). Therefore, putting aside the analytical evaluations, the artifact's utility is demonstrated by considering the scheduling of road maintenance tasks as a concrete scenario. By expounding its utility for road authorities, one can demonstrate the necessity of the smart road condition monitoring service and the monetary potential for an intermediary providing this service.

As mentioned in the problem definition, road authorities require accurate information regarding road conditions in order to efficiently schedule maintenance actions. The goal is to find an optimal strategy for minimizing the costs of operation and maintenance actions, as well as the costs for gathering information concerning road conditions (Watanatada et al. 1987). It is at the discretion of the authorities to decide when to perform which maintenance action, and when to perform which type of road inspection, and especially when to purchase which type of road condition information. Spending more money on road inspections allows for a more efficient scheduling of maintenance actions and thus saves maintenance costs (and vice versa). Formally written, this is a problem of finding an optimal policy in an accessible, stochastic environment with a known transition model. The environment is accessible since it can be observed by inspections and influenced by maintenance actions. It is stochastic since the deterioration over a period of time and the rehabilitation through a maintenance action are not always the same. Such an optimization problem can be described as a Markov decision process (MDP) (Puterman 1994; Gao and Zhang 2013). Solving this MDP addresses the trade-off between maintenance costs and inspection costs.

The frequency of performing highly accurate road condition inspections is constrained by high costs. However, if provided with the smart service described in this article, the MDP would be subject to fewer constraints since road condition information could be purchased at nearly arbitrary time intervals. Even though this also imposes costs, it undoubtedly results in a higher degree of freedom to act. This higher degree of freedom allows for the development of a more efficient, and therefore cheaper, policy. The demonstrated cost reduction potential is a clear incentive for road authorities to utilize the smart road condition monitoring service. At the same time, this encourages the provision of such a crowdsensing-based service by a new intermediary.

From the intermediary's point of view, a way to monetize the service would be to charge for spatio-temporal information packages. The road authority can purchase information regarding the condition of rural roads in their administrated road network for the previous year on a monthly granularity. The utility of the service depends on the intervals at which the road authority would purchase road condition information. The pricing regime should reflect these varying degrees of utility to the customers by providing discounts if information packages are purchased more frequently. Assuming an appropriate degree of spatio-temporal information coverage, such a value-based pricing regime is feasible, since information is an intangible asset (Hand and Lev 2003).

In addition to the road authorities and the intermediary, utility for the crowd must be ensured, as the crowd as a data provider is of fundamental importance for the crowdsensing-based road condition monitoring service. Creating utility for the crowd, and thus instilling the willingness to install the requisite software and providing the gathered data, can be supported by different concepts.

Zhang et al. (2016) distinguish between entertainment, service, and money as possible incentives for mobile crowdsensing. Entertainment as an incentive aims at ensuring that the sensing itself is not understood as a mere task, but that the participants enjoy taking part. In the sense of gamification, a common approach would be to award points corresponding to the distance traveled, enabling competition among the participants. Using a service as an incentive would mean that the participants gain access to a service in return for collecting and providing data—most likely, the same service made possible by the crowdsensing. Since the crowd consists of road users in this case, the participants are potential customers of the smart service anyway. Thus, there is no need to provide further examples for service-based incentives. Finally, another way to motivate the crowd to participate is through monetary incentives. Accordingly, payments can be on the basis of the recorded kilometers or the quality of the recording performance.

Conclusion and outlook

We designed a smart road condition monitoring service based on crowd-sensed data that introduces a new service provider into the value-added network. To do this, we took into account the needs of road authorities and road users with regard to the accuracy and timeliness of the road condition information. The new service provider acts as an intermediary between the crowd and the road engineering companies as service providers, on the one hand, and the road authorities and road users as service customers, on the other. Our modeling approach was described in the form of a service map by following the design science approach. We evaluated our approach by implementing an example prediction service by the intermediary. Based on this, we also implemented a spatio-temporal hotspot analysis of crowd-sensed data as an example of the prescriptive analytics service. The results show that, given the new intermediary, road authorities can be provided with frequent and accurate road condition information. The technical feasibility of the service was demonstrated by analytical evaluations. The benefits for the road authorities and for the intermediary were demonstrated by a descriptive evaluation based on a road maintenance scenario. The research question, how a service integrator can meet the information demands of road authorities and road users by orchestrating data services from several individual data providers (in a timely and accurate manner), was thus answered.

In addition to the artifact itself and the analytical and descriptive evaluations, our work also contributes to the research fields of service science (service integration and service maps) and crowdsensing. We demonstrated how service maps could be applied in the context of crowdsensing to design a new service that integrates individual data providers. We implemented individual analytical services to prove the technical applicability of the smart, crowd-based road condition monitoring service by considering accelerometer and gyroscope sensors for predicting the IRI. The designed service map serves as a general framework for different road condition metrics and sensors. Since service science is also about providing frameworks for value cocreation between entities as they interact, the designed artifact further contributes to the knowledge base, as it is a framework for value cocreation between engineering companies, the crowd and the integrator (Spohrer and Maglio 2010).

Despite demonstrating the utility of our artifact and the contribution of our research through the aforementioned evaluations, we are aware of limitations. We proposed that the framework should be generalizable. However, deploying other sensors, such as cameras and microphones, and considering road condition metrics other than the IRI must be evaluated with regard to the reliability of the predictions. Even though we provided a descriptive evaluation of the artifact's utility to road authorities and to the intermediary, an extended summative evaluation in a naturalistic setting and with experts from the field should be performed (Venable et al. 2016). This would show whether human stakeholders recognize the utility of the smart service, which is essential for its acceptance. An extension of the summative evaluation should also address economic questions quantitatively. Thus, the degree of utility for each stakeholder could be determined. Economic aspects regarding service monetization and provider incentives are also of importance with regard to the applicability of the service. In addition to an extended evaluation, further research can investigate the possibility of payment regimes reflecting the quality of the data provided. Additionally, the spatio-temporal coverage of measurements, and thus the supply and demand of crowd-sensed data, can be considered by providing dynamic payments to the sensing participants. Besides monetary incentives, gamification-based approaches should be considered in future research to answer the question of how road users can be motivated to provide their data.

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