Rolling Vibes

**CONTINUOUS TRANSPORT
INFRASTRUCTURE MONITORING**

FATJON SERAJ

Rolling Vibes

Continuous Transport Infrastructure Monitoring

ROLLING VIBES
CONTINUOUS TRANSPORT INFRASTRUCTURE
MONITORING

DISSERTATION

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by

Fatjon Seraj

born on July 7, 1977
in Vlore, Albania.

Graduation committee:

Chairman:	Prof. dr. P.M.G. Apers
Supervisor:	Prof. dr. ir. P.J.M. Havinga
Supervisor:	Prof. dr. ir. T. Tinga
Co-supervisor:	Dr. ir. N. Meratnia

Members:

Prof. dr. ir. R.N.J.Veldhuis	University of Twente
Dr. ir R.A. de By	University of Twente
Prof. dr. P. Lukowicz	German Research Center for Artificial Intelligence
Prof. dr. G.W. Kortuem	Delft University of Technology

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*The goal is to turn data into information
and information into insight.*

Carly Fiorina

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Abstract

Transport infrastructure is a *people to people technology*, in the sense that is build by people to serve people, by facilitating transportation, connection and communication. People improved infrastructure by applying simple methods derived from their sensing and thinking. Since the early ages, humans knew that infrastructure should avoid certain amount of vibration that affected either the passenger or the carriage. They achieved that knowledge using the human body sensing capabilities. In fact the human body is the perfect complex sensor node, sensing a wide range of bandwidths, starting from vibrations to the radio waves.

Nowadays, specific systems are available that can determine the quality of the road surface by means of special measurements in a somewhat more systematic way. However, a new paradigm of crowd based sensing is emerging, as a result of the smart mobile device revolution. These devices are becoming as ubiquitous as the people that carry them. As daily commuters travel around, their senses are trained to detect road pavement irregularities, uncomfortable turns, potholes, road joints, rail road bumps, stations, accelerations, deceleration and so on. If a human can detect these situations just by classifying the vibration level, why cannot the smartphones in their pocket do the same thing? And same as people do, what a smartphone skipped or missed learning can be compensated by more and more knowledge provided by an army of smartphones participating in infrastructure monitoring. This naive reasoning gave rise to further reasoning and studying the nature of vibration resulting in four long years of research and this thesis.

Smartphone based crowd-sensing is not a new concept, there have been previous attempts to make use of this all-around technology. However, a major challenge is the fact that the smartphones are very diverse, have no accurate sensors, and are non-deterministic by nature. On the other hand being ubiquitous, they provide the ability to continuously measure because of the available processor, memory, and (wireless) communication tools.

Correct handling of these inaccuracies and unreliable data has been a central theme of the research. Like people, intelligence, learning systems, and additional observations are used to compensate for inaccurate and incomplete observations. The signals measured from the transport infrastructure are a function of four parameters time, distance, temporal frequency and spatial frequency, each with a limited degree of accuracy. In this thesis, we show that with the help of advanced signal processing and machine learning, despite the many inaccuracies in the observations, we can accurately reflect road quality and type of damage. The information obtained by the smartphone sensors is first processed locally by wavelet decomposition methods and useful features

are calculated which are then clustered. To compensate for the position inaccuracies, a new aggregation and visualization algorithm has been developed. In addition to a more or less direct measurement of the vibrations, an indirect method is also used, taking into account the driver's driving behavior.

The algorithms, methods, and techniques have been extensively tested and evaluated in various scenarios (for motor vehicles, cyclists, and wheelchairs). Certain indicators are computed to reflect the *state-of-the-art* requirements. In addition to measuring the quality of the road surface, the quality of railroad track geometry has also been measured.

Samenvatting

De weginfrastructuur is technologie voor en door mensen gebouwd. Het zorgt ervoor dat mensen en goederen effectief en efficiënt vervoerd kunnen worden. De kwaliteit van de weginfrastructuur is dan ook erg belangrijk, en het beperken van oneffenheden en ongewenste trillingen is altijd belangrijk geweest voor zowel het comfort van de bestuurder, als voor het beperken van schade aan het voertuig. Een slecht wegdek leidt vaker tot ongelukken, en geeft schade aan voertuigen. Slecht wegdek en spoedreparaties leiden tot files, waardoor vertragingen en vervuiling toenemen.

Vroeger gebruikte men voor het meten van de wegkwaliteit de menselijke sensor. Mensen kunnen dergelijke bewegingen en trillingen namelijk heel goed waarnemen, en zijn in feite een ideale sensor geschikt voor een zeer breedbandig spectrum van waarnemingen. Tegenwoordig zijn er specifieke systemen beschikbaar die met behulp van speciale meettrucks de kwaliteit van het wegdek op een wat meer systematische manier kunnen bepalen. Het nadeel van dergelijke systemen is dat ze een momentopname weergeven aanzien deze meetsystemen op meer dan jaarlijkse basis de wegen bemeten.

Heden ten dage zijn er door de technologische ontwikkelingen van de mobiele telefoon echter alternatieve mogelijkheden om de wegkwaliteit te meten en te verwerken. Dit onderzoek richt zich op de vraag welke mogelijkheden er zijn om met smartphones in voertuigen schades aan het wegdek in een vroeg stadium te detecteren, waarna vervolgens adequate maatregelen kunnen worden genomen. Door de inzet van deze zogenaamde crowd sensing technologie kan de monitoring van infrastructuur sneller en efficiënter worden uitgevoerd. In een dergelijke aanpak gebruiken we de alom aanwezige telefoons om de infrastructuur min of meer continue te monitoren.

Crowd sensing met mobiele telefoons is niet een nieuw concept, er zijn al eerdere pogingen geweest om gebruik te maken van deze alom aanwezige technologie. Een grote uitdaging is echter het feit dat de telefoons heel erg divers zijn, geen nauwkeurige sensoren hebben, en van nature niet deterministisch zijn. Aan de andere kant hebben ze wel de mogelijkheden voor continue meten vanwege de aanwezige processor-, geheugen-, en (draadloze) communicatiemiddelen.

Het op een adequate manier omgaan met deze onnauwkeurigheden en onbetrouwbare data is een centraal thema geweest van het onderzoek. Net als mensen wordt gebruik gemaakt van intelligentie, lerende systemen, en aanvullende observaties om onnauwkeurige en incomplete waarnemingen te compenseren. De signalen en waarnemingen aan de weginfrastructuur leveren parameters op in tijd en afstand, en in het frequentiespectrum in tijd en plaats, elk met een beperkte mate van nauwkeurigheid. In dit proefschrift laten we

zien dat met behulp van geavanceerde signaalprocessing en machine learning er ondanks de vele onnauwkeurigheden in de waarnemingen, er toch een goede weergave kan worden gegeven van de wegkwaliteit en het type schade. De informatie verkregen door de sensoren in de telefoon worden eerst lokaal bewerkt middels Wavelet Decomposition methodes. Hieruit worden bruikbare features berekend, die vervolgens worden geclusterd. Om de onnauwkeurigheden van positiebepaling te compenseren is een nieuw aggregatie en visualisatie-algoritme ontwikkeld. Er wordt naast een min of meer directe meting van de trillingen, ook een indirecte methode gebruikt, waarbij het rijgedrag van de bestuurder wordt meegenomen.

De algoritmes, methodes, en technieken zijn uitgebreid getest en geëvalueerd in diverse scenario's (voor motorvoertuigen, fietsers, en rolstoelen), waarbij naast het meten van de kwaliteit van het wegdek, ook de kwaliteit van rails is gemeten.

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1

Introduction

Transportation infrastructure is in the core of our civilization. It allows us to travel faster and further, to explore vast territories, and to meet each other. We are continuously on the move and the need to be mobile all the time has lead to important innovations that have shaped our current transport infrastructure. Everything started with narrow trails our ancestors used for hunting. As animals got domesticated, the trails got wider to accommodate the traffic. The invention of the wheel allowed people to increase their traveled distances and transported load. However, to be able to ride smoothly, the wheeled carts required flatter roads.

Ancient Romans were the first to build a sophisticated road network, known as "Roman roads" [1]. These were roads built to connect the entire territory of the Roman empire to the Capital Rome. The saying "*Omnes viae Romam ducunt*" ("all roads lead to Rome") has stemmed from this history. These roads were impeccably designed, were carefully built to accommodate drainage systems, and were paved with stones. They, however, required maintenance to withstand the traffic and weather conditions. Romans developed a maintenance system, in which different road segments were assigned to regional prefectures to be periodically inspected for defects or other anomalies.

It was until the Industrial Revolution that transportation network started to resemble to the one we know today. It was John Loudon McAdam (1756–1836) who abandoned the ancient Roman technology of stone pavements and built the first modern highways leveling and paving them with macadam, a mixture of sand and tar [2]. The road is elevated from the plane to drain the water from the surface. The vehicles increased the need for paved roads to reduce the damage to both the road and the vehicles and to increase the passenger comfort.

In addition to the road transport infrastructure, the economical development of the Industrial Revolution period also relied heavily on the new railroad transport infrastructure. Although they are wheeled vehicles, trains travel through

designated steel rail tracks acting as a low friction surface. The quality of the railroad tracks is characterized by the track geometry. Track geometry represents a three-dimensional geometry of track layouts [3]. The geometry is characterized by the construction of the railroads itself. Deviation or failure of any of the track elements will result in geometry changes and severe safety consequences.

1.1. Transport infrastructure maintenance strategies

Probably the roads and railroads will become obsolete as digitization advances, but until then people will use them and want to ride on them fast and safe. Meanwhile, the world road transport infrastructure length and the number of vehicles are estimated to be 35 million km [4], and 35 vehicles per 1000 people [5], respectively. On the other hand, the world railroad transport infrastructure as per 2014 was measured to be 1 million km [6].

Many studies and surveys are made on the topic of roadway deficiencies and their impact on safety and economy [7]. With the advancement of the automotive industry, transport infrastructure improved to allow higher travelling speeds. However, higher speeds cannot tolerate road imperfections and defects. To ensure a high safety standard for passengers, vehicles, and goods the maintenance should be adequate and up-to-date.

Transport infrastructure may wear and its condition deteriorate over time due to various factors related to, among other things, their location, load/traffic, weather, engineering solutions, and materials. Road anomalies such as pot-holes can affect the driving experience and the overall state of the vehicle. For instance, in a well developed country like the United Kingdom, drivers spend £2.8 billion for axle and suspension failure on a yearly basis [8]. This type of failure constitutes one third of mechanical issues on the UK roads [8]. The British authorities currently pay more than £50 million in compensation claims due to poor quality of UK roads [8].

Developed countries monitor their infrastructure through specialized systems called Pavement Management Systems (PMS). The Pavement Management System consists of a set of tools that assists authorities to develop cost effective strategies for evaluating and maintaining road pavements in working condition [9]. PMSs have two major components, i.e., (i) a complete database, which stores all available information about the current and historical pavement condition, road transport infrastructure, and traffic, and (ii) a set of statistical and predictive tools to allow authorities to evaluate existing and future pavement conditions and to identify and to prioritize infrastructural investments. In the Netherlands since the introduction of PMSs in early 1989, 75% of all of the local authorities, municipalities, and provinces, have utilized a PMS [10]. Developing countries often lack this kind of technology and the *know-how*.

1.1.1. Reactive maintenance vs. Preventive maintenance

Maintenance of transport infrastructure is one of the prime concerns of both central and local governing bodies. This maintenance is currently performed either in a reactive manner, i.e., repairing the damaged segments, filling pot-hole, replacing damaged rails or in a preventive manner, i.e., repairing assets that are expected to break down, adding a layer of asphalt, etc..

Reactive maintenance is the process of reacting to failed infrastructure elements by restoring their intended function. Generally this type of maintenance is a costly operation. Failures are unpredictable and required resources (including budget, labor, and material) to repair them may not always be available or may come with extra costs. While an infrastructure element may be repaired using a reactive maintenance, its life will not be maximized.

Preventive maintenance encompasses procedures and tasks that help prevent or mitigate the consequences of failure of the infrastructure elements. Generally, preventive maintenance is ruled by owner's manuals, industry standards, environmental conditions, infrastructure safety and sensitivity, and know-how, among other things. As illustrated in Figure 1.1, it is less expensive to keep a road in good condition than to repair it once it has deteriorated. This makes the predictive maintenance more important and more popular. However, both of these strategies require continuous monitoring and availability of fine-grained in-situ measurements.

Figure 1.1: Costs associated with preventive vs. reactive maintenance of the road pavement condition related to the pavement deterioration curve

1.2. Transport infrastructures

Inland transport infrastructure includes roads and railroads, among other things. In what follows, we explain the main characteristics of these two transport infrastructures.

1.2.1. Road transport infrastructure

Roads are designed for specific purposes reflecting the distance of travel, the traffic flow, as well as travel speed. Categorization of the road transport in-

frastructure follows a well established hierarchy, which categorizes them in accordance to their functionality and capacities [11].

Figure 1.2: Road hierarchy, responsible authority and access to propriety

Figure 1.2 illustrates a hierarchical division between types of roads into motorways, arterial, collectors, and local roads. Motorways sit at the top of the hierarchy. These type of roads are designed for higher speeds and long uninterrupted distances. Arterial roads accommodate traffic external to and across specific areas while the sub-arterial roads accommodate traffic between specific areas and the arterial roads [11]. Collector streets are located within the specific areas providing indirect and direct access for land uses within the specific areas to the road network. These streets should carry no traffic external to the specific areas [11]. Local roads (streets) have lower speed limit and higher pedestrian priority. Their functionality is to provide direct access to local neighborhoods, they may be unpaved [11], as well. Pedestrian infrastructure is also used by vehicles such as bikes and wheelchairs, which still require a smooth pavement to reduce the accidents and well-being of their operators (drivers).

The Netherlands in addition has a very dense bike path network consisting of 35,000 km [12] of dedicated high speed and normal city lanes. Bike lane pavement monitoring is usually carried out by on-site visual inspections. The obtained information, sometimes combined with cyclist reports, are used for planning maintenance activities. Otherwise maintenance is carried out periodically.

Most countries will develop the roads in this hierarchical fashion, with motorways at the top level and local roads at the bottom level. This hierarchy is quite natural as higher we move into road level more demanding are the design requirements and specifications for that particular level. However, the hierarchy is established in a way that combines the design and functionality throughout the network. This allows different road authorities to manage the same geographical area with different levels of road functionality.

The performance quality of the road pavement is influenced by the following factors [13]:

- Traffic - the road is projected and constructed to withstand a certain amount axle load (one axle load being $80kN$) per unit of time. If that number is exceeded, the pavement will deteriorate faster.

- Water - A poorly sealed road pavement can cause the water to leak into the subgrade and destroy the underlying gravel structure.
- Subgrade - Consists of the gravel material on top of which the asphalt layer is applied, its duty is to support the wheel load. A softer subgrade layer can cause the surface to flex and the asphalt layer to break.
- Construction quality - failure to construct the roads according to standards for their used intentions may result in premature failure of the road.
- Maintenance - No matter how well the road is built, it will deteriorate over time based on the aforementioned factors. A proper maintenance at the right moment can preserve road quality and increase road lifetime.

Road pavement distresses can be categorized as follows:

- Cracking: Fatigue (crocodile) cracking, longitudinal cracking, transverse cracking, edge cracking etc.
- Surface deformation: Rutting is the common form of surface deformation. It can be described as the displacement of pavement material that creates channels in the wheel path. Very severe rutting will actually hold water in the rut [13]. Other forms of surface deformation are corrugation, shoving, depressions.
- Disintegration: Disintegration of the pavement surface results in potholes and patches.
- Surface defects: Ravelling happens as the result of the loss of material from the pavement surface. Excessive asphalt cement results in bleeding which reduces the skid-resistance of the pavement. Whereas polishing is a result of traffic wearing off asphalt aggregate on the pavement surface resulting in very low friction [13].

1.2.2. Railroad transport infrastructure

Railroads differ from conventional roads on which vehicles run on flat surfaces. Railroads are specific type of railed or track roads allowing rail vehicles, also known as rolling stocks, to travel through in a lower friction resistance fashion. Railroads offer a set of advantages over other transportation modes, providing a more reliable way of transportation, which is less concerned about weather conditions and its operation is more certain as it relies on fixed routes and schedules. It allows higher travel speed and passenger/good transportation than other transportation modes, thus being more economical. However some of these advantages can result in disadvantages that can lead into infrastructural failures.

Track failure can happen as a result of individual failure or co-occurrence failure of the following main components [14]:

- Deterioration of the track sub-structure, e.g., road bed, sub-ballast, drainage.

- Deterioration of the track super-structure, i.e. rails, joints, switches (including all their sub-components), and the ballast layer.
- Deterioration of the track geometry, i.e. horizontal and vertical track profile.

The following seven factors contribute to the track deterioration [15–19]:

- Wheel loads – is by far the primary cause of the track deterioration.
- Track characteristics - track configurations and condition of track components play a critical role in resisting track deterioration and greatly affect dynamic wheel load.
- Design and construction errors - errors during the design and construction phase influence the materials and manufacture and are the initial source of track deterioration.
- Quality of materials and manufacture - The quality and the performance of the materials used and the quality the manufactured components are crucial for railroad condition.
- Maintenance - Inadequate or erroneous maintenance operation or ill prepared maintenance plans have huge impact on railroad conditions.
- Environmental factors - temperature and precipitations in addition to the wheel loads can increase the deterioration rate.
- Terrain - any variations in the terrain structure, which constitutes the base of the railroad track, will influence the speed of track deterioration.

1.3. Transport infrastructure maintenance indicators

Currently infrastructure maintenance activities are performed by evaluating a number of health and condition indicators. These indicators are not necessarily similar for all infrastructure types (e.g. roads, bike paths, and railroads). In what follows, we explain the most commonly used indicators per infrastructure type.

Providing a real-time overview of health and condition of the ground infrastructures can substantially reduce the costs of maintenance as well as accident rates.

1.3.1. Road transport infrastructure

The main characteristic of a road pavement is the roughness. To determine the road roughness, road engineers measure the profile of the road. A profile is a segment of road pavement taken along an imaginary line. Usually the longitudinal profiles are subjects of study because they show the design grade,

roughness, and texture of a profile [20]. Road roughness is defined by the American Society of Testing and Materials (ASTM) [21] as: “The deviations of a pavement surface from a true planar surface with characteristic dimensions that affect vehicle dynamics, ride quality, dynamic loads, and drainage, for example, longitudinal profile, transverse profile, and cross slope”. Equipment and techniques for roughness estimation are usually categorized into the following [20]:

- Road and Level surveys performed by a survey crew.
- Dipstick profiler, which is a hand-held device commonly used for calibration of complex instruments.
- Response type road roughness meters (RTRRMS), consisting of transducers that measure accumulated suspension motions.
- Profiling devices, which are usually sophisticated inertial reference systems with accelerometer and laser sensors to measure the vehicle displacement.

These systems are usually implemented in specialized vehicles called ARAN (**A**utomatic **R**oad **AN**alyzers).

Road engineers mainly use pavement roughness as the most important feature to predict further deterioration of roads and to plan ahead their maintenance. International Roughness Index (IRI) [20] is a well-known and most commonly used indicator by road engineers. It is an index obtained by calculating the response of the quarter car model over a longitudinal road profile [20]. IRI is measured in m/km , which represents the accumulated vertical deviation of one kilometer longitudinal road profile. In the Netherlands, there are 139.000 km of public roads and the cost of using ARAN for measurement campaigns is around €40/lane km. Therefore, it is a challenge to perform these measurements in a frequent basis.

1.3.2. Railroad transport infrastructure

Railroad network maintenance is more complex than road maintenance. The railroad track inspection is carried out by special measurement trains that measure condition of different track components for different operating speeds. The measurement campaigns have to be scheduled. Some measurement campaigns are carried out during night hours in order not to interfere and obstruct the busy traffic flow and operations of the railroads. Track geometry trains (TGC) inspect the track for faults related to the alignment of the track gauge, cross-level, curvature, rail profile, among other things. These faults influence the measurement trains by generating vibrations and forces that are able to derail trains from the track, leading to severe accidents.

1.4. Crowd based transport infrastructure monitoring

The introduction of smart mobile devices took the world by storm. These ubiquitous mobile devices equipped with sensing, computation, and wireless com-

munication capabilities gave rise to a plethora of crowd sensing applications that collect, process, and share information. Smartphones, the undisputed leaders of the smart device kingdom, can perform a rich environmental sensing thanks to the increasing set of cheap and powerful sensors, such as accelerometer, digital compass, GPS, microphone, and camera. The combination of numerous sensing capabilities with the computational power can be utilized to monitor the surrounding environment and infer human activities and contexts.

Researchers and engineers have started to exploit the potential of these devices from a crowd-sensing point of view. Surging applications are showing the feasibility of crowd sensing in daily activities starting from noise pollution to road and traffic monitoring, opportunistic networking, activity monitoring, safety and emergency aid, etc.. These humongous amount of crowd-sensed and processed data fulfills all the five criteria, called 5 V-s, i.e., Volume, Variety, Velocity, Veracity and Value to enter and enhance the BIG DATA domain [22].

- **Volume** refers to the vast amount of data generated continuously by the vehicle equipped with smartphones all over the place.
- **Variety** refers to the different types of data collected with different smartphones over different roads with different vehicles.
- **Velocity** refers to the velocity at which new data is collected and transmitted in real time.
- **Veracity** refers to the quality of the data. Smartphone sensors have their own limitations in terms of being noisy and uncertain and imprecise.
- **Value** refers to the ability to transform these data into valuable knowledge about the state of the infrastructure.

Smartphone-based crowd sensing for transport infrastructure involves measurement of large-scale infrastructure data related to maintenance indicators, by a large group of individuals with their smartphones. Crowd sensing can be participatory or opportunistic. The former requires user input (for example to input the location of a pothole), while the latter relies solely on the device's capabilities [23].

The benefits of using a crowd-based sensing and monitoring approach are twofold, for both users and authorities. Users are more concerned about passenger safety and ride comfort, giving them the incentive to contribute to identification of all annoying infrastructure anomalies such as potholes on the road or the centrifugal forces on railroad turns. Authorities will benefit from availability of appropriate and frequent indicators, arriving from all the participating smartphones, covering a wider territory and providing continuous information about the state of the road. This will facilitate a rapid reaction and decision making for maintenance activities. Figure 1.3 illustrates a functionality chart for the crowd sensing-based transport infrastructure maintenance. The participants can interact with the system manually or the smartphone

can non-intrusively handle all the workload. In this thesis we only address the following infrastructure health indicators: Pavement roughness, Pothole Detection, Driver Behavior, railroad Cant elevation, Grade, Twist, Vertical and Horizontal Alignment.

Figure 1.3: Functionality chart of crowd sensing-based transport infrastructure maintenance

From a crowd sensing point of view, one can argue that drivers/cyclists/train passengers carrying a smartphone equipped with inertial sensors can measure vehicle displacements and rotations caused by road roughness and track irregularities. This type of monitoring is a paradigm shift, from being solely delivered by specialized equipment and engineers to consider the vehicles and smartphones as sensor nodes and processing powerhouses that can provide useful information and indications about the state of the transport infrastructure monitoring.

Smartphones use inertial measurement units (IMU) to detect the movements and orientations. An inertial sensor can be described as an encapsulated observer within a completely shielded case aiming to determine the position changes of the case with respect to an outer inertial reference system. Inertial sensors exploit inertial forces acting on an object to determine its behavior. The basic dynamic parameters are acceleration along some axis and the angular rate. External forces acting on a body cause an acceleration and/or a change of its orientation (angular position) [24]. IMUs of a smartphone come in the form of **Micro Electro Mechanical System** (MEMS) chips, namely Accelerometers, Gyroscopes and Magnetometers. MEMS-based sensors are considered whole wrapped, calibrated and tested products, ready to be used as modular component into consumer or industrial devices. The accuracy is driven by application or system requirements.

1.4.1. Challenges

Albeit that smartphones incorporate a handful and useful sensors, the fact is that these sensors are designed for user experience rather than highly accurate sensing. An industrial high-end sensor should be highly accurate, reliable, and robust, whereas these characteristics are compromised in smartphone sensors. The quality of a sensor on such devices is low. Using smartphone

as sensor nodes for infrastructure monitoring confronts us with the following challenges:

- **Sensor quality** –Smartphone inertial sensors are cheap MEMS sensors with declared accuracy settings.
- **Low sampling rate** –The sensor sampling rate is quite slow, the faster the vehicle travels, the longer the distance between two consecutive samples becomes.
- **Localization** –Geo-location estimation accuracy of the smartphone GPS chip is in the order of 8 meter, which is larger than the state of the art measurement vehicles.
- **Uncertainties** –The position of the sensor several layers distant from the transport infrastructure surface (i.e., the wheels, damping system, vehicle saloon, smartphone holder).
- **Latency** – Smartphone Operating System (OS) is a Non-Real Time Operating System (non-RTOS). This introduces latency in sampling rate as well as delays or interrupts of the monitoring services.

When designing crowd sensing-based systems utilizing smartphones, there are some considerations to be carefully taken into account. First of all, it should be noted that the system will be executed on top of a non-RTOS, which prioritize execution of services based on their sensitivity and available resources. This makes smartphones non-deterministic. This means that, for example the sensors may report random time lags between samples or services may compute the measurements with a delay based on the process hierarchy. This will also constrain the other system requirements. Making participation of any user (device) in the process of infrastructure monitoring easy, a consistent monitoring model is needed. In other words, the system should be available for a large-scale heterogeneous deployment.

Sampling Rate

According to the Nyquist sampling theorem [25], if a function $Y(t)$ contains no frequencies higher than B Hz, it is completely determined by giving its ordinates at a series of points spaced $1/(2B)$ seconds apart. In other words, Nyquist sampling rate is the rate at which the signal must be recorded in order to accurately reconstruct the original signal. A given pothole on a given road will present different frequency signatures depending on the speed of the vehicle passing through it, even though it has a fixed spatial signature. For example, a smartphone sensor with a sampling rate of 100Hz can measure sinusoid with frequencies up to 50 Hz. Figure 1.4 shows a road segment measured with a smartphone sampling at 100Hz traveling with three different speeds, the distance between two consecutive sampling increases as the speed increases, consequently losing the information about anomalies in between them. However, that signal is compromised by the high level of noise related to

the inaccuracy of the sensor and position of the device. Additionally, smartphone sensors also measure other multiple signals not related to the infrastructure geometry, for example wheel and engine revolutions. These continuously changing frequencies affect the nature of the signal, making it transient and non-stationary. Based on the Nyquist theorem, if the speed of the vehicle is too high, the frequency representing the pothole will also be too high and as such will not be recorded by the smartphone.

Figure 1.4: 100Hz sampling rate over a 1.1m segment with different speeds

1.5. Research objectives and hypothesis

The main focus of this thesis is on design and evaluation of transport infrastructure monitoring solutions that are cheap, robust, real-time, and easy to deploy also can act as alternative/complementary to the current technologies for transport infrastructure monitoring. To this end, the focus is to investigate the potential of smartphone-based crowd sensing. We provide a framework and associated services/functions that work consistently over all infrastructure types being them roads, railroads or bike paths. Considering the limitations and constraints of the smartphones themselves, we develop smart, reliable, and robust algorithms and methods for signal processing, learning, big data aggregation, and visualization.

1.5.1. Research questions

The main research question to be answered is:

How can the information collected from smartphone sensors traveling over different transport infrastructures, be translated into meaningful and accurate quality indicators that are useful for both infrastructure engineers and infrastructure users?

In order to answer this question and address the aforementioned challenges, the following encapsulated sub-questions need to be answered first:

- *What is the nature of transport infrastructure anomalies, which sensors capture them best and how is the sampled sensor data associated with them?*

- *How to handle the uncertainties and errors associated with smartphone sensors?*
- *How to reduce the impact of speed on the quality of sensor measurements?*
- *What techniques are needed to efficiently process the sampled smartphone data and to translate them into accurate and reliable maintenance indicators?*
- *How to efficiently combine and represent the results from each individual smartphone into precise geolocation on the transport infrastructure?*

1.5.2. Research hypotheses

We start our research from the following hypothesis:

- **Hypothesis 1.** *Despite the fact that vibrations caused by the infrastructure irregularities and transmitted to the smartphone traveling inside the vehicle can attenuate by the damping structures of the vehicle, sensors can capture the wavelengths, signatures, and nature of these irregularities.*
- **Hypothesis 2.** *Using state-of-the-art signal processing and machine learning techniques, vibrations and rotations of the vehicle caused by the infrastructure irregularities can be classified into corresponding anomalies on the infrastructure geometry.*
- **Hypothesis 3.** *The uncertainties introduced by low quality sensors and GPS inaccuracies can be diminished by aggregating the results from multiple measurements over the same segment of the transport infrastructure.*
- **Hypothesis 4.** *The speed of the vehicle probe modulates the sensor measurements in frequency and amplitude.*
- **Hypothesis 5.** *Driver behavior on the road can be translated into valuable knowledge about the state of the infrastructure.*

Building upon the aforementioned hypotheses, our approach starts with identifying the targets, challenges, and solutions. Being a complex field, dominated by decades long research and field experience with sophisticated equipment, the maintenance indicators are well identified and classified for each infrastructure type.

Because crowd sensing is only possible with participation, the incentive to participate should be encouraged with rewards to the participants. In this particular field, the participants are drivers or passengers who are looking forward for a smooth and safe ride being in their car, on the train, on the bicycle or even on wheelchair.

1.6. Thesis contributions

Overall contributions of this thesis consist of a framework and associated techniques and methods to allow real-time collaborative monitoring of transport infrastructure using smartphones and to provide accurate and reliable maintenance indicators. To this end, this thesis has the following contributions:

- **Contribution 1:** *A system for road transport infrastructure anomaly detection and classification.*

We present a smartphone-based anomaly detection system capable of detecting and classifying road anomalies. The system takes into consideration a set of constraints that limit the performance of the system and provides the workarounds to overcome these constraints.

- It introduces a signal processing method to reduce the speed dependency over the sampled data.
 - It provides supervised and unsupervised machine learning techniques for anomaly detection and classification.
 - It includes a driver behavior detection algorithm to reduce uncertainties introduced by different driving styles.
 - It includes a clustering algorithm to narrow down the location estimation of the detected anomaly.
- **Contribution 2:** *A smartphone-based framework and associated services for determining transport infrastructure maintenance indicators.*

While anomaly detection on the road infrastructure is important to address all the irregularities, it falls into the category of reactive maintenance. This type of maintenance is much more costly than preventive maintenance. Therefore we present a framework targeting infrastructure and maintenance authorities and engineers for real-time and continuous monitoring of the transport infrastructure geometry. The framework deals with the problem of calculation of maintenance indicators for roads and railroads using inaccurate smartphone data and data representation. By providing insight in the time evolution of the deterioration, the monitoring system will enable preventive maintenance to be executed.

- **Contribution 3:** *A fast and robust aggregation and visualization algorithm for data reduction of crowd sensing-based infrastructure monitoring application.*

We present an aggregation and visualization algorithm to alleviate the impact of GPS inaccuracies for continuous monitoring of transport infrastructures using smartphones. The lightweight algorithm is implementable as centralized on the cloud or local on the smartphone. The algorithm is particularly suitable for situations with scarce prior knowledge of the infrastructure.

1.7. Thesis organization

This rest of this thesis is organized as follows:

We will start in Chapter 2 with reviewing the state-of-the-art methods and techniques implemented and used to monitor the road and railroad transport infrastructures. Part of this discussion will affect related alternative research and work conducted in this field using the smartphone-based monitoring and their primary concerns including passenger comfort, road anomaly detection, driver behavior analysis, road roughness analysis, and accessibility analysis for wheelchair users.

Chapter 3, presents an overview of our system for transport infrastructure monitoring. Further on we discuss all of our framework functionalities and services provided by our system, starting from anomaly detection, driver behavior, continuing with road roughness and track geometry. The system architecture is discussed to describe the potential of the framework in different scenarios. We also discuss all the components of our system architecture such data handling blocks, algorithms and data dissemination blocks.

Chapter 4 presents our map matching and aggregation approach for crowd based transport infrastructure monitoring.

Chapter 5 focuses on the system capabilities for road anomaly detection, called RoADS. We will discuss the data acquisition, signal processing, feature extraction, machine learning classification algorithms, driver behavior as tool to enhance anomaly detection as well as clustering algorithms proposed to couple together related detection.

In Chapter 6, we describe continuous transport infrastructure health monitoring called RoVi. We start with describing the automatic transportation mode identification algorithm, advancing with the description of infrastructure health indicator calculations and evaluating the proposed system.

Chapter 7 describes the conclusions and possible directions for future work. Another implementation of the proposed framework in the context of infrastructure monitoring for people with disabilities forced to move with a wheelchair, is presented as an Appendix to this thesis. Figure 1.5 illustrates the organization of this thesis and the relationship among different chapters.

CHAPTER 1	CHAPTER 2	CHAPTER 3	CHAPTER 4
MAINTENANCE STRATEGIES	STATE-OF-THE-ART	SYSTEM OVERVIEW	MAP MATCHING
1.REACTIVE	1.ARAN	SENSORS	DELAUNAY TRIANGULATION
2.PREVENTIVE	2.UFM TRAINS	1.ACCELEROMETER	AGGREGATION
		2.GYROSCOPE
		3.GPS	CHAPTER 5
TRANSPORT INFRASTRUCTURES	ANOMALY DETECTION	LIMITATIONS	ROAD ANOMALY DETECTION
1.ROAD	SMARTPHONE BASED	1.SAMPLING RATE	ANOMALY DETECTION
2.RAILROAD	DRIVER BEHAVIOUR	2.ERRORS	SIGNAL PROCESSING CLASSIFICATION
3.PEDESTRIAN	PASSENGER COMFORT	3.LATENCY	DRIVER BEHAVIOUR
	PEDESTRIAN	SERVICES	ANGLE CALCULATION CLASSIFICATION CLUSTERING
TRANSPORT INFRASTRUCTURE MAINTENANCE INDICATORS		1.ANOMALY DETECTION
	ROAD ROUGHNESS	2.DRIVER BEHAVIOUR
1.ROAD	TRACK GEOMETRY	3.ROAD ROUGHNESS
2.RAILROAD		4.TRACK GEOMETRY	CHAPTER 6
CROWD-BASED INFRASTRUCTURE MONITORING		ARCHITECTURE	TRANSPORT INFRASTRUCTURE INDICATORS
1.SMARTPHONES		1.CONTEXT MANAGER	TRANSPORT MODE IDENTIFICATION
2.BIG DATA		2.SENSOR MANAGER	ADAPTIVE SIGNAL PROCESSING
3.CHALLENGES		3.INFRASTRUCTURE MONITOR MANAGER	EVALUATION
		4.AGGREGATION
		5.DATA TRANSMISSION
ROAD RAILROAD PEDESTRIAN REACTIVE MAINTENANCE PREVENTIVE MAINTENANCE			

Figure 1.5: Thesis organization

2

Transport infrastructures monitoring approaches

Efficient transport infrastructures are vital economical and social components of every country. They provide access to the markets, increase productivity, provide labour mobility, and enhance the social relation between communities. To ensure an optimal transport infrastructure network, rapid and effective maintenance strategies are of prime concern. Industries have developed sophisticated machinery that allow thorough monitoring of the state of the infrastructure providing important health and maintenance indicators. These machines provide geometry and structural indicators allowing the engineers to address prematurely the problem in a preventive fashion.

2.1. Transport infrastructure monitoring systems

The definition of infrastructure according to the Dictionary is: "the fundamental facilities and systems serving a country, city, or area, as transportation and communication systems, power plants, and schools" [26]. Transport infrastructure that involve mechanical vehicles as a transportation mean can be divided into ground, water and air infrastructures. These types of infrastructures allow the transport or movement of people, animals, and goods through the land using roads or railroads, ships, and aircrafts, respectively. Only ground transport needs a man-made network infrastructure to connect two points, whereas the vessels and planes on water and air transport have no travel restriction in terms of direction or range.

2.1.1. High-end road infrastructure monitoring systems

As previously stated in the [Introduction](#) Chapter, roads are split into four categories, each of them having different responsible authorities. Each of these road types is identified in Pavement Management Systems (PMS) with its sub-

characteristics [9][27]. A short list of the main relevant characteristics of the road segments from the measurement point of view include:

- Geographical location, which includes the road name, mileposts, and link /node location (indicating where milepost nodes are linked with each other.)
- Directions being bidirectional or unidirectional. **L** is usually used for the Left side of the road and **R** for the Right side of the road.)
- Number of lanes for each direction.
- Number of nodes for each lane.

Quality of road segments is measured by the following parameters illustrated on Figure 2.1:

- Road roughness, which is the vertical unevenness on the road that causes excessive vertical vibration to the vehicles (and the passengers).
- Rutting, which are uneven depressions of the pavement, which during the wet seasons can accumulate water and cause serious safety problems.
- Crossfall, which is the transverse slope of the road surface. Straight road segments should have the center of the road higher than the shoulder, whereas on a curve the slope of road should point toward inner part of the curve. Crossfall should be enough to ensure a proper drainage to the road surface.
- Pavement distress, which are cracks or wear leading to more serious problem if left untreated.

Specialized Automated Road Analyzer (ARAN) vehicles equipped with sophisticated measurement tools drive through roads and measure their roughness (i.e., the deviation of a road surface from a true planar surface).

2.1.2. High-end railroad infrastructure monitoring systems

Railroads are complex engineered mechanical structures consisting of a number of elements with their well defined characteristics. The failure or deterioration of any of those elements can cause changes in track geometry that will affect the safety and the comfort of the passengers or goods and in extreme cases derailment of the train from the tracks.

Figure 2.2.a illustrates the components of a railroad track on a curve and on a switch segment. Switches shown in Figure 2.2.b are important parts of the railroad network as they allow the train to switch between different tracks to change the destination. During the switch period, the train shakes as passing through the Point (Tongue) and the Frog. As a rail element has a certain length, rail joins are used to connect two rails together. These points where transition load is more concentrated are prone to failure. The sunken ballast profile can change the track geometry, horizontally and vertically resulting in Twists which is another indicator of track geometry.

Figure 2.1: ARAN vehicle measuring road pavement

Figure 2.2: Railroad components a) on a cant b) on a switch

Railroad track characteristics are expressed by the following main parameters [28] also shown in Figure 2.3:

- Vertical profile, which is the rail-head profile in the longitudinal vertical plane. Also known as "Top", "Longitudinal level", and sometimes "Surface".
- Horizontal profile, which is the track centre-line profile is defined as the variation from the design profile in the horizontal plane normal to the tangent. Also known as "Alignment" or "Line".
- Gauge, which is the distance between the inside faces of the rail heads, measured a fixed distance down from a straight line joining the rail crowns.

The fixed distance varies a few millimetres on different railways usually no more than 14 mm.

- Crosslevel, which is the height of the left rail above the right rail, measured in the transverse vertical plane. It is often referred to as "CANT", or "Superelevation". Cant is very important for passenger comfort.
- Twist, which is the deviation in rail height that causes the rails to warp and the train to rotate and have accidents.
- Curvature, which is the spatial rate-of-turn in the horizontal plane. Various units, are used but a 20-metre versine equivalent is preferred.

Railroad track geometry measurements are carried out through manual inspections with a profiler, using a special measurement train, or using a coach attached to a normal train. To the best of our knowledge, only very few papers report on calculating or inferring the track geometry using alternative methods or equipment. The Deutsche Bahn [29] in Germany equipped their Hi-Speed ICE2 restaurant cars with a system called Continuous Track Monitoring (CTM), which consists of multiple inertial sensors at three different points of measurements for different purposes. These points of measurements are:

- Accelerometers on axle boxes (vertical and horizontal) – for assessment of track geometry of short wavelength,
- Accelerometer on the bogie frame (horizontal) – for assessment of rolling behavior,
- Accelerometer inside the coach body – for assessment of rolling behavior and ride comfort.

It is interesting to note that tests have shown a good correlation between track geometry quality and vehicle reaction of the car body [29]. The standard deviation of the vertical track quality measured by sensors on the axle boxes has shown a high correlation with the running behavior measured by the accelerometer sensor inside the coach body.

Figure 2.3: Track geometry indicators for railroad transport infrastructure, alignment and cant

2.2. Infrastructure crowd sensing

Crowd sensing-based transport infrastructure monitoring is not a new notion in the field of infrastructure monitoring. Its potentials have been studied and exploited for a long period of time by many research teams, resulting in many applications and systems built upon this sensing paradigm. Proposed works cover a wide spectrum of infrastructure monitoring spanning from the impact of infrastructure to the passenger comfort, anomaly detection, mutual effects of infrastructure and its users on the driver and passenger behavior, transport mode classification, infrastructure geometry measurements, traffic monitoring, and hazardous infrastructure segments detection.

It is worth mentioning that during the literature review we could not identify any work related to crowd sensing-based railroad or bike path monitoring.

2.2.1. Passenger comfort

Lin et al. [30] proposed a Comfort Measuring System (CMS) for public transportation systems, exploiting data collected through participatory phone sensing to measure the comfort level of each vehicle ride. The sensed data are mashed up with the authorized data of the public transportation system (i.e. license plate numbers, the vehicle routes and route numbers, as well as information identifying the transportation agency names and the types of the vehicle) to provide detailed insights into the comfort levels of vehicle rides. The proposed trajectory matching algorithm is validated with real data collected from the CMS system deployed in Taipei City. It has been shown that it can achieve a hit rate of 93.7%. Statistical analysis has shown that only 17% of bus rides in Taipei are considered uncomfortable with no significant differences between different bus agencies. The authors found out that the comfort level varies a lot among the bus services provided by the same agency, and smaller buses are the least comfortable.

RESen [31] propose Riding Experience Sensor (RESen), i.e., a system for sensing and evaluating the riding experience based on crowd sourcing by a smart phone. With the help of the acceleration and gravity sensors of the smart phone, RESen can sense and partition the riding experience into horizontal and vertical with arbitrary orientation of the smart phone. RESen then evaluates the riding experience in order to improve the driver's behavior and to provide a comfortable travel plan for users.

Tan et al. [32] presented a comprehensive study of an Android application for smartphones to evaluate the riding quality for public transport through mobile cloud sensing. The proposed approach is based on a mobile-cloud scheme which mainly focuses on the measurement of two aspects: the driving behaviors (such as accelerate, break, turning, etc) and the environmental contexts (such as vibration, noise, crowding, etc). Several methods for data processing are presented. Leveraging crowd sensing possibilities, authors claim an increase in both accuracy and robustness: driving behavior detection accuracy increases from 69% (single smartphone) to 91% (7 smartphones).

2.2.2. Road anomaly detection

Some anomalies are temporary on the road, some are intentionally designed and some are results of pavement deterioration. The most famous and annoying road anomalies are potholes. Potholes are often results of neglected or bad constructed road segments [33]. Water and freeze-thaw cycles are the main culprit for pothole creations. They form during fall-winter seasons far from the usual inspections carried during the dry seasons. Other type of road anomalies are the rotten manholes that deteriorate on their edges and fall below the pavement surface. "Crocodile cracks" are distressed pavement surfaces that brake and sink, when left untreated the hole pavement surface will decay, they increase the vibration level and noise when driven upon them. Driving vehicles are exposed to heavy vibrations and rotations when drive over these anomalies, hence drivers tend to avoid them by swerving around them.

The following works show that inertial sensors of the smartphones alone can be used to detect road surface anomalies. The focus of these works are, however, solely on detection of manhole/potholes because potholes are the main concerns of the driver community and also they are relatively easy to detect based on the energy of the signals of inertial sensors. Both theoretical research and experiments suggest that potholes are created as a result of distresses and poor drainage of road surface [33]. Detection and correct classification of these distresses will improve the long-term availability and life-time of the road pavements. All existing pothole detection solutions face one major issue, namely the vehicle velocity. The same road anomaly generates different frequencies and amplitudes being driven over with different speeds. Figure 2.4 illustrates the signal generated by a manhole when approached with low and high speeds.

Figure 2.4: A 2-second sample of the vertical accelerometer signal when the vehicle drives over a manhole at low speed (in left) and twice the speed (in right)

An important issue worth mentioning is the data labeling methods used to annotate the road anomalies. It is crucial to train an anomaly detection algo-

rithm with the right anomalous segments to achieve high detection accuracy.

Pothole Patrol (P^2) [34] uses a high resolution 380Hz accelerometer and a GPS device attached to the vehicle dashboard to collect data and to detect the potholes. Data are transferred to a central server for further processing. Clustering is used to increase detection precision. Five filters are used, among which the so-called *z_peak* that aims to distinguish potholes from other high-amplitude road events. Filter *speed vs. z_ratio* is introduced to filter out signals with a peak less than a factor t_s times the speed of travel. The labeling technique is based on a trained labeling expert sitting inside the vehicle and pressing keyboard keys corresponding to a set of predefined anomaly types as they occur.

Nericell [35] uses the microphone and GPS of a Windows smartphone in conjunction with a high resolution Sparkfun WiTilt accelerometer clocked at 310Hz to monitor traffic and road pavement. They use the same technique as in P^2 [34] to threshold the acceleration signal and to deal with varying speed. The novelties consist of introducing another filter named *z_sus* for speeds $< 25\text{km/h}$, arguing that the same anomaly form different shapes for different speeds and virtual orientation of the phone. They, however, do not mention the labeling technique they used.

Perttunen et al. [36] use a Nokia N95 mounted on the wind-shield of a car. The accelerometer data was sampling at 38Hz and the GPS of the phone was used to collect the location data. Their algorithm classifies the anomalies into two classes, i.e., mild anomalies and severe anomalies. A method of linear regression is introduced to remove the linear dependency of the speed from the feature vector. Labeling is performed with a camcorder attached to the headrest of the front passenger seat, however they realised this method was unreliable to detect the anomalies. A FFT transformation of the signal is performed to extract frequency domain features and to label the data by plotting together the power spectrum and time domain data. A question related to this work is how a 38Hz accelerometer sensor can generate 17 frequency bands with 1.4Hz bandwidth.

Tai et al. [37] use an HTC Diamond smartphone with accelerometer sampling at 25Hz and a GPS. The data collected by a motorcyclist riding strictly at two different speeds, 30km/h and 40km/h were pre-processed by the device and sent to a centralised server for classification. Two classification procedures were performed, one to detect the anomalies and the other one to rate the road pavement quality using a predefined model of a smooth road. Labeling was performed by the motorcyclist having a microphone and stating the type of anomalies being encountered while riding. An algorithm was used to map the audio label to the nearest anomaly event captured by the accelerometer.

Wolverine [38] is an extension to the work of Nericell [35]. Authors describe it as a non-intrusive method that uses sensors available on the smartphones. The work proposes an improved algorithm based on using accelerometer, GPS, and magnetometer sensor readings for traffic and road condition detection. Particular focus is to identify braking events as the breaking frequency indi-

cates congested roads. The bumps on the roads were used to characterize the type of road. A classification algorithm based on SVM was used to classify the breaking events. The evaluation of the effectiveness of the proposed method is based on experiments conducted on the roads in Mumbai.

The aforementioned works considered signal transformation and machine learning techniques for the detection of anomalies. Using these complex algorithms does not leave much room, in terms of power consumption and processing capabilities, for further analysis of the anomalies on the smartphone platform. Despite the claims of high detection rates, the accuracy remains still an issue.

2.2.3. Driver behavior analysis

Analysis of driver behavior is being extensively researched and applied in modern automotive industry. It is mainly studied and researched as a way to detect driver actions behind the steering wheel with the focus to prevent accidents and to decrease accident impact on passengers. Researchers have been facing the problem of creating a driver profile out of vehicles sensor data in order to predict or to detect events. These systems are built using different approaches. The state-of-the-art solutions are based on systems and data received from vehicle sensors. Examples include (i) the Advanced Driver Assistance System (ADAS) [39], which utilizes driver behavior prediction and a broad range of sensors to assist, complement, or substitute the driver accordingly to the traffic situations and (ii) the Lane Departure Warning system (LDW) [40], which warns the driver intending to leave the lane.

In addition to the solutions based on vehicle sensors, several research groups have contributed to the topic of road anomaly detection using inertial sensors using external smart devices [34–38] [41]. All these studies, however, were conducted making the assumption that, the driver will pass through all the anomalies. However this is not always true.

Figure 2.5 illustrates four different scenarios where the driver may deviate the normal trajectory to avoid facing the anomaly on the road.

None of the existing studies on road anomaly detection considered the scenario in which the driver deliberately skips the anomalies and how this activity will affect the overall results.

Driver behavior is also studied for its impact on traffic load, fuel consumption, and resource management. Studies have found a correlation between the driver behavior and accident rates. Researches studied the effect of Driving Monitoring Recorders (DMR) to increase driver awareness and reduce traffic accidents [42, 43]. Paefgen et al. [44] concluded that even though smartphones accuracy was inferior to the state-of-the-art in-car solutions, the results show a correlation between the road type and the detected driver behavior.

Some works such as [45] and [46] have applied the Hidden Markov Models algorithms on smartphones data combined with augmented signals collected from the car OnBoard Diagnostics (ODB) to detect and predict the driver behavior from the maneuver states. Eren et al. [47] studied analysis of driver behavior

Figure 2.5: Example scenarios in which the normal trajectory may not be followed to avoid hitting road anomalies

using smartphones to detect critical driving situations on the road. Johnson et al. [48] used accelerometer and gyroscope signals of a smartphone together with a Dynamic Time Warping (DTW) [49] algorithm to detect potentially aggressive driving events. They state that using the accelerometer or gyroscope alone is not possible to distinguish between some turns, such as left turn and a U-turn.

2.2.4. Road roughness analysis

Monitoring state of the road pavement using cheap inertial sensors sparked the interest of the researcher community when smartphones started to become mainstream. Researchers reason that *mega-texture* and *roughness* have frequency components that can be measured by the inertial sensors of the smartphones. Gonzales et al. [50] showed through simulations that vibration and road profile can be related linearly through a transform function. By calibrating the measurements over a known profile, it is possible to define the transform function and to calculate the Power Spectral Density (PSD) of the profile. It was noted that driving closer to calibration speed will yield more accurate results. The sensor noise will decrease the profile prediction for wavelengths below 0.04 cycles/meter but will perform very well regardless of the noise for wavelengths above 0.1 cycles/meter.

Douangphachanh et al. [51] investigated the relationship between magnitude of the vibration frequencies and the road roughness. The data was collected using smartphones placed loosely in different locations inside the vehicle. The reference road roughness was obtained using the Vehicular Intel-

lignant Monitoring System (VIMS) capable of detecting IRI for speeds above 20 km/h. They concluded that road roughness condition is linked to a linear function of magnitude of acceleration and average speed. They also confirmed that mega-texture and roughness cause vibrations at the frequency range of 40-50Hz. This frequency range can be easily covered by modern smartphone sensors.

Roadroid [52] is a mobile application measuring the road quality and correlating it with IRI. Developers of Roadroid found out that (i) speed and vehicle type significantly influence the roughness results, and (ii) model of the accelerometer sensor and sampling rate significantly influence quality of data. At the present time Roadroid cannot calculate IRI as precise as the ARAN vehicle but the huge amount of data collected indicates a correlation of about $RC\ 0.9 * IRI + 1.8$. Authors planned to further develop Roadroid in future and to offer the system as good as Highway Design and Maintenance Standards Model (HDM). Schlotje et al. [53] tested an implementation of Roadroid in Kiribati to test the performance of the solution in the Pacific region. The report concluded that IRI calculation is conducted for 1 second intervals and is consistent when traveling with the same speed. This accuracy, however, drops in case of traveling with different speeds. Calculating the IRI over 100 m segments would have been appreciated as this would have been in line with the state-of-the art standard. However, within the accuracy of +/-20% IRI Roadroid satisfied the need. The work presented in [52] and [53] do not provide any comparison between their obtained results and the real IRI values. They also do not provide any details about their signal processing approach to reduce the speed dependencies.

Islam et al. [54] describe an Android application called *Roughness Capture*, which consists of a data collection application for recording accelerometer data sampled at 100Hz. The collected data is then used offline to calculate the pavement roughness using the ProVAL software [55]. The authors concluded that the IRI values measured with their smartphones were similar to those measured by the profiler with a few outliers on the smooth segments of the road. However on the rough segments of road, the smartphones resulted in lower IRI values than the real ones. Authors also mentioned the dampening impact of vehicle suspension on vertical acceleration readings.

SmartRoadSense [56] is an Android application that calculates the Power Spectral Density of the road elevation profile. The accelerometer data is collected at a sampling rate of 100Hz. The roughness calculation was conducted on windows of 100 samples, corresponding to the GPS sampling rate. Authors offer a model, in which the Power Spectral Density is calculated by filtering the dampening effect of the tires and suspensions and other stationary noise using Linear Predictive Coding (LPC). The authors collected the smartphone calculations in a central server for visualisation purposes. The work fails to compare the obtained results with the state-of-the art road roughness standard values.

As mentioned in [57], most of the previous works have focused on detection

of road anomalies as they will affect drivers comfort (or cars lifetime). However, maintenance/ construction companies responsible for monitoring transport infrastructures are not particularly interested in finding location of these road anomalies but, rather, on providing maintenance indicators/standards. Current solutions do not suffice for this purpose.

2.2.5. Accessibility analysis for the wheelchair users

Another field of interest, in which crowd sensing-based infrastructure monitoring using smartphones have been studied is related to monitoring accessibility of the infrastructure for disabled and wheelchair users. Wheelchairs are rolling vehicles prone to vibrations caused by the pavement roughness, varying in intensity and amplitude. From a mechanical point of view, they are simple rigid mechanical models, without springs, thus allowing the vibration to be transmitted all over the frame, including the user himself also exposing certain categories of wheelchair users to additional collateral injuries.

Research has been conducted utilizing accelerometers to measure whole-body vibration (WBV) and wheelchair vibrations in both manual and motorized wheelchairs [58] [59]. Conclusions from these studies indicate that wheelchair users are exposed to risks of secondary injuries due to whole-body vibration.

Cooper et al. [60] studied the effect of suspensions to reduce the shock and vibration on seat and footrest. They found out that suspensions reduced the shock and vibrations, although they are not clearly superior to traditional designs. Attempts to reduce the WBV without compromising the wheelchair features introduced new type of wheel constructions. Vornik et al. [61] compared those wheels in terms of vibration and spasticity in people suffering from Spinal Cord Injury (SCI). They concluded that the new wheel type did not absorb or reduce the vibrations caused by path roughness. These studies indicate that accelerometers are capable of measuring the concerned vibrations induced by path roughness and the vibration level do not differ substantially among wheelchair models. The aforementioned works used different methods for data analysis. Frequency analysis was used in [60] and [59], Root Mean Square (RMS) of the vertical acceleration was used in [58] and [61], and analysis of variance (ANOVA) was used by [61]. Although wheelchairs are not equipped with accelerometers, their users use smart-phones equipped with GPS and inertial sensors. Accelerometers and gyroscopes sense all the vibrations and angular changes and smart-phones can handle, process, and share that information. Ergo, allowing wheelchair users to use and update that information in real time. They can measure the path roughness, ramp or curb angle, bumps, the presence of an elevator. They can safely plan their trip according to their needs, avoiding paths and directions not suitable for their specific condition.

OurWay [62] is a collaborative route planner in which users individually rate segments of paths, to provide information tailored to wheelchair user needs and preferences. It is a smartphone-based route planner application but does not use inertial sensors. The path segments are subjectively and manually rated by the users. Authors of [62] conclude that the users were not much interested

to give feedback about the route and they only wanted the best route. This adds a strong motivation for automatic solutions in which the user does not need to give feedback.

WeGoTo [63] focuses on obstacle denunciation on a wheelchair path, involving the use of smartphone inertial sensors. It presents a flowchart diagram describing the decision making algorithm. The algorithm classifies different states (i.e., fall, propelling, and turning) with subjective results (i.e. easy, medium, and hard) for the wheelchair based on orientation and accelerometer data. However, no results and evaluations were presented. Although the paper illustrates a generic chart for sensor fusion there is no indication whether the authors implemented another Kalman filter algorithm or used Android API to obtain the orientation. Explanation is missing regarding the smartphone position relative to the vehicle frame and how, if, the reorientation is performed. The safety regulations states that the sidewalk crossfall should not be more than 2° . To this end, the paper fails to discuss the accuracy of the angle estimation. The same can be said for the ramp and slope angle calculations. The paper mentioned frequency analysis and signal energy but did not elaborate further at which frequency bins that energy was concentrated.

2.3. Summary

Following the aforementioned analysis of the state-of-the-art infrastructure monitoring solutions from both high-end and crowd sensing point of views, Table 2.1 presents a comparative table summarizing features of each of the crowd sensing based solutions.

State-of-the-art methods provide a highly accurate indicator set of transport infrastructure health. However, they cannot provide granular temporal information for the infrastructure state between consequent measurements. All the proposed crowd-sensing based approaches focus on road pavement anomaly detections assuming that drivers will always hit the anomaly. Thus, underestimating the high probability of driver behavior on escaping the anomaly. Driver behavior is never studied as means to enhance road anomaly detection. The effects of speed and sampling rate are also overlooked and underrated.

Table 2.1: Feature comparison for the related work

	Group	Sensor						Smart phone	Signal procc.	Detection Classif.	Nr. Anomaly Classes	Dealing with Uncertainty	Labelling
		acc Hz	gyro Hz	GPS Hz	Mag.	audio	video						
[34]	PotholePatrol	380		1					TD	ML	2	✓	Text
[35]	Nericell	310		1		✓		✓	TD	Threshold	1		Text
[36]	Pertunen et al.	38		1				✓	FD	SVM	2		Video
[37]	Tai et al.	25		1				✓	FD	SVM	2		Audio
[41]	Mednis et al.	100		1				✓	TD	Threshold	5		Text
[38]	Wolverine	50		1				✓	TD	SVM	2		Text
[64]	RoADS	93	100	1				✓	WT	SVM	3	✓	A/V/Text
TD:time domain, FD: frequency domain, WT: wavelet transformation, ML: machine learning.													
Works related to Driver Behaviour													
		acc	gyro	GPS	Mag.	CAN BUS	Audio Video				Nr. Activities		Purpose
[47]	Eren et al.	✓	✓	✓	✓			✓	DTW	Bayesian	2		Aggressive driving
[44]	Paefgen et al.	20	3.3	1				✓	TD	Threshold	4		Manoeuvre detection
[48]	Johnson et al.	25	25	✓				✓	DTW	Threshold	12		Manoeuvre detection
[65]	Seraj et al.	100	100	1				✓	WT	Threshold	8		Manoeuvre detection
[66]	Li et al	100	100	1		✓		✓	WT				EV efficient driving
[67]	Van Ly et al.			✓		✓		✓	TD	SVM	4		Manoeuvre detection
[67]	DriveSafe	100			✓		✓	✓	OpenCV,TD	Threshold	5		Manoeuvre detection
[68]	SmartLDWS			✓			✓	✓					Lane partition
DTW: Dynamic time warp, EV: electrical vehicle													
Works related to Road Roughness Index													
		acc	gyro	GPS	Mag.	Roughness Indexes		Profile length		Speed dependent			IRI Comparison
[52]	Roadroid	✓		✓		eIRI		1 sec		not reported		✓	
[56]	Smartroadsense	✓		✓		R		1 sec.		not reported			

3

System overview

To be able to measure relevant data for transport infrastructure monitoring and to obtain maintenance indicators in a crowd sensing-based fashion, a set of requirements (both from hardware and software point of views) needs to be satisfied. Heterogeneity of smartphones and various uncertainties associated with the mainstream off-the-shelf hardware combined with the fact that inexperienced participants will take active part in the data collection process necessitate that the system accounts for dynamicity, uncertainty, unreliability, and heterogeneity of the environment, participants, and technology.

Smartphone market is dominated by the major Operating System providers, namely, iOS and Android from Apple and Google, which provide Software Development Kits (SDK) and Application Programming Interfaces (API) to allow developers to build applications for the smartphones ecosystem and to interact with components, services and applications. They also provide specifications for hardware components and modules (e.g. sensors, location and networking modules). Whereas iOS maintains uniformity of sensor components over all its smartphones, quality of Android devices are varied by a myriad of manufacturers covering the whole price spectrum.

Being a system implemented on a heterogeneous and dynamic smartphone platform, our crowd sensing-based transport infrastructure monitoring system needs to satisfy a number of hardware and software requirements. In what follows, we present these requirements and describe the overall system architecture including its functionalities and services.

3.1. Sensing requirements

Most of the signals encountered in science and engineering are analog in nature. That means that these signals are functions of a continuous variable, such as time or space, and usually take on values in a continuous range [69]. Physical signals are measured by domain specific devices called sensors. For

example, sound and vibration signals are recorded by a microphone and an accelerometer, respectively. However, what is recorded by these devices is only an approximation of the true event due to the constraints and errors associated with the sensors themselves. Nonetheless, if the sensor errors are less than the required accuracy they can successfully observe the given event. Our system requires the following sensors, which majority of modern smartphones fulfill them:

3.1.1. Inertial sensors

Accelerometer is an inertial sensor capable of measuring the vector quantity of magnitude and direction of the proper acceleration. In other words, it measures the rate of change of velocity of the smartphone with respect to time. Currently accelerometer sensors of smartphones are primarily used for re-orienting the screen and its content based on the sensed orientation of the device.

Instantaneous acceleration is measured over an infinitesimal time interval and, as expressed below, is the limit of average acceleration when the time interval approaches zero. This equals the derivative of velocity with respect to time.

$$a = \lim_{\Delta t \rightarrow 0} \frac{\Delta v}{\Delta t} = \frac{dv}{dt} \quad (3.1)$$

Velocity is the derivative of displacement r with respect to time and is expressed as:

$$a = \frac{dv}{dt} = \frac{d}{dt} \frac{dr}{dt} = \frac{d^2 r}{dt^2} \quad (3.2)$$

Linear acceleration denoted by la is the measured acceleration a without the gravity component g . Android provides the linear acceleration as the output of a *synthetic sensor*, i.e., a virtual sensor, being calculated based on the input of acceleration, gyroscope, and magnetic sensor. In fact Android implements a Kalman filter to reduce the errors introduced by the sensor noise and provides output of a number of *synthetic sensors*. When smartphones are equipped only with the accelerometer sensor, the linear acceleration la can be calculated by first calculating the gravity vector g . Considering the fact that gravity is somehow constant (i.e., not changing very fast), it can be approximated applying a low-pass filter on a with response α :

$$\begin{aligned} \alpha &= \frac{t}{t + dt} \\ g &= \alpha * g + (1 - \alpha) * a \\ la &= a - g \end{aligned} \quad (3.3)$$

This implies that availability of accelerometer sensor alone is enough to have an estimation of the linear acceleration and angle of rotation. However, availability of the gyroscope and magnetometer sensors will increase the accuracy of displacement and rotation utilizing sensor fusion techniques.

Gyroscope is an inertial sensor capable of measuring the change of rotational (angular) velocity ω , the speed at which the smartphone is rotating. In other words, it measures the angular ϕ displacement with respect to time.

$$\begin{aligned}\omega &= \frac{d\phi}{dt} \\ \vec{\phi} &= \int \vec{\omega} dt\end{aligned}\tag{3.4}$$

Gyroscope is used in the smartphones to increase the accuracy of detecting the device rotations and to help developers build services and applications that respond more accurately to the user input.

3.1.2. GPS sensor

Speed of travel affects the measurements in both frequency and amplitude, therefore it is very important to reduce that dependency by adapting methods to the speed. Locating the infrastructure segments and providing the measurements conforming to the standards is a requirement posed by the authorities.

Using a device equipped with GPS (**G**lobal**P**ositioning **S**ystem), one may assume that speed and position will always be available. However, this is not the case with the current GPS chips found in today smartphones. GPS sensors suffer from the so-called TTFF (**T**ime **t**o **F**irst **F**ix) delay. In order to ensure short TTFF, availability of a clear line of sight and a stable position are essential. This is not always the case, especially for a travelling vehicle. In smartphones, the TTFF is improved by introducing a technology called A-GPS (Assisted GPS) [70]. A-GPS requires an active data connection with a mobile network operator to receive a preloaded list of available GPS satellites for a given location location. In addition to shortening the TTFF, A-GPS also improves GPS location accuracy by providing the cell tower localization.

3.2. Services

As mentioned in previous chapters, monitoring different transport infrastructure types requires different services and maintenance indicators. This means that all these services need to be part of a multi-purpose framework that various services can be implemented individually for domain-specific applications. Figure 3.1 demonstrates a synopsis of our proposed framework system and corresponding application stack representing various services. The framework is proposed as a skeleton providing a set of methods and techniques to build the required services and applications related to the transport infrastructure monitoring. The following chapters will provide more details regarding these techniques and algorithms as well as their evaluation in different application scenarios. In what follows, we describe these services and their underlying principles briefly.

Our system provides three main services related to the road transport infrastructure monitoring, namely anomaly detection, driver behavior analysis,

Figure 3.1: Smartphone based transport infrastructure monitoring application stack

and road roughness analysis. Railroad track geometry service handles the calculation of track geometry indicators

Anomaly detection

Anomaly detection refers to techniques that identify anomalous data observations or events which diverge from expected patterns, behaviors, or events in a dataset. These non-conforming patterns are often referred to as anomalies, outliers, discordant observations, exceptions, aberrations, surprises, peculiarities, or contaminants in different application domains [71]. Anomalies can be classified into three categories [71]:

- Point anomalies - When individual data instances differ from the rest of the data. Example of such anomalies are the potholes, speed-bumps, manholes etc.
- Contextual anomalies - When data instances are anomalous only in a specific context. For example consider a driver forced to swerve around a pothole. This swerve can be considered anomalous in comparison with other type of turns, because the driver is expected to drive straight in that particular segment of roads.
- Collective anomalies - When the data instances *per se* may not be anomalous but their evolution over time or space makes them anomalous. An example is the continuous monitoring of the road pavement, although the pavement does not exhibit any visual deterioration, the pavement layer in time wears off and the deterioration trend over time shows the anomalous segments.

Anomaly detection in the context of transport infrastructure monitoring refers to identification of all unexpected phenomena, situations, and events faced on these segments/pathways. From a naive-reasoning point of view, anomalies on the transport infrastructure generate excessive vibration when a vehicle runs over them. These anomalous events are expected to exhibit high

amplitude vibrations and can be classified as *point anomalies*. This hypothesis is, however, only true if the entire vehicle fleet rolls on the the infrastructure with the same speed. However, since this is not always the case, monitoring the amplitude of the vertical vibration alone is not enough to correctly detect and classify them. Accurate anomaly detection requires *a priori* knowledge (labels) about type of frequently occurring anomalies, their representation in the dataset, as well as transport infrastructure segments corresponding to both normal and anomalous situations.

Driver behavior analysis

Driver behavior on the road is characterized by drivers attitude towards the speed and the turns. Road engineers divide the road curves into two categories, i.e., horizontal and vertical curves. Horizontal curves change the direction of the vehicle from left to right or right to left, while vertical curves or slopes change the direction of the vehicle from up to down or down to up. A maneuver on the road is in essence a curve or a set of curves, therefore the focus of identifying maneuvers is on the horizontal changes of vehicle direction.

A driver will follow a curve in the following cases: (i) when the vehicle follows a turn on the road, (ii) when the vehicle changes the road lanes, (iii) when the vehicle overtakes another vehicle, a pedestrian, or a cyclist, (iv) when the vehicle drives on a curvy road, (v) when the vehicle aims to avoids a (risky) anomaly on the road pavement.

Curves can be permanent in the form of road turns or temporal in the form of swerves. Temporal curves are caused by the driver decision to overcome temporal situations on the road, for instance overtaking events or swerving to avoid objects, debris on the road, dead animals, tree branches, etc.

Our driver behavior analysis service calculates all vehicles jaw axis angles and classifies the curves into different categories based on the angle of the vehicle swerve and the complexity and signature of the swerve elements. The information inferred from the driving behavior analysis service can be used to enhance the detection of infrastructure anomalies, to infer hazardous infrastructure segments, to study the behavior of young drivers, among other things.

Road roughness analysis

The roughness of the road, which is the main maintenance indicator of the road transport infrastructure, is characterized by the surface texture. The road surface texture is divided into different categories based on the wavelength of the texture. Figure 3.2 shows different texture categories and how they affect the vehicle/tire interaction.

While micro-texture is essential for the tire footprint to grip the asphalt, mega-textures are indication of pavement wear and damage. The vehicle vibrations are caused by mega-textures affecting the suspension and tire loads. Mega-textures have wavelengths of 5cm or more. The ride quality is affected by the mega-textures with wavelength above 1m.

The International Roughness Index (IRI) is a mathematical model that calculates the roughness based on the response of the sprung and unsprung mass

Figure 3.2: Different wavelengths generated by various road damage types and their impact on a vehicle

Figure 3.3: Quarter car model and effect of micro- and mega- textures on the car

of the quarter of the car. Figure 3.3 shows a quarter car model and the effect of micro- and mega- textures on the car.

Our road roughness analysis service calculates the roughness corresponding to the IRI by utilizing a set of adaptive signal decompositions, from which only the vibrations with wavelengths corresponding to the roughness are extracted. Because IRI is an index of the ratio between the overall vertical deviations and the profile length, the service allows creation of specific profile lengths widening the GPS error bounds.

Track geometry analysis

Railroad tracks consist of two parallel metallic rails spaced from each other with a certain width called *GAUGE*. As shown in Figure 3.4.a, the standard gauge width is 1435 mm. The locomotion of the trains is possible due to the friction between their metallic wheels with the rails. Whenever a train enters a curve, the track should provide a certain degree of slope for the train to resist the lateral forces. To provide the necessary slope, the outer rails should be placed higher than the inner rail. The difference between the two rails in the curvature is called *CANT*. The angle of the cant is calculated using Equation 3.5, where h_t is the rail elevation and $2b_0$ (as shown in Figure 3.4.b is the width between the center of the rails around 1500 mm. Cant is calculated when the coach enters and leaves the curve as well as all the twists for different wavelength.

$$\varphi_t = a \sin \frac{h_t}{2b_0} \quad (3.5)$$

Figure 3.4: Train track gauge and cant

In the case of passing through a curve, the train coach is exposed to two accelerations, i.e., (i) lateral acceleration a_y parallel to the track plane and (ii) vertical acceleration a_z perpendicular to the track plane. All the information regarding track geometry (cant, twist, curvature) as well as vertical profile can be measured and derived from the accelerometer and gyroscope readings, as well as the location of track segments from the GPS chip. The service calculates all the roll and pitch angles on the railroad track by differentiating the curvatures based on their length. This allows to classify curvatures based on their wavelength.

3.3. System architecture

This section explains the architectural modules of our crowd sensing-based system for transport infrastructure monitoring using smartphones. Most of the architectural modules share different services to decrease the architecture complexity and computation / communication overhead that can be overwhelming and minimize the benefits provided by the smartphone platform. Figure 3.5 shows the system architecture, showing that it consists of the following main modules:

- Context Manager module allows controlling various types of transport infrastructures and deciding how the sensor data will be processed.

- Sensor Manager module, which manages and controls access to the sensing components.
- Infrastructure Monitor Manager module will process and calculate maintenance indicators based on the infrastructure type selected by the Context Manager component.
- Aggregation module to allow aggregation of the maintenance indicators and their location on the smartphones in situations, in which selected infrastructure segments are periodically monitored by the same device. This is done to further reduce the computation complexity on the cloud/server side.
- Data Transmission module to assist the system to communicate with the cloud as well with other smartphones opportunistically, utilizing WiFi and GPRS.

Figure 3.5: System architecture diagram

In what follows we explain the above-mentioned modules.

3.3.1. Context manager module

Participants of the transport infrastructure monitoring can utilize a variety of transportation modes. Each transport infrastructure necessitates certain sensors, functionality and services to be used. Context manager module is responsible for the management of the transportation mode context. Monitoring features can be contextualized in three ways:

- User input, when the participant based on his needs selects the type of the infrastructure being monitored.
- Application, when the proposed framework services are being used to develop or input information to other specific systems or platforms. In such cases the context is managed or predefined by exterior sources.

- Activity recognition, when the device itself recognizes the transportation mode utilizing the input from Sensor manager and appoints the corresponding services according to the infrastructure being used.

3.3.2. Sensor manager module

Access to the sensing components is provided by the smartphone OS. Although the OS allows arbitrary sampling rates, there is no guarantee that the sampling rate will be correct. Lack of a sensor will result in service limitations, for example the lack of gyroscope will provide limited results regarding vehicle orientation which will consequently lead to incorrect angle calculations (as the angles will be calculated by the accelerometer axis tilt). However, the system provides the sensing requesting a list of available sensors. Once the sensor list is available and the sensors of interest are present, the system will investigate the maximum rate at which a sensor can acquire data. Sensing allows the system to tap different sensors, even those are not directly related to the infrastructure state. For example light sensor can determine the light intensity and can be used to study the environment characteristics of the infrastructure.

While the data is being processed, the raw data can also be stored in a local database and sent to the cloud whenever a WiFi connection is available. As mentioned earlier, the raw sensor data is affected by uncertainties and noise associated with sensor hardware, environmental factors, and infrastructure maintenance indicators. Building algorithms and implementing services based only on the sensors raw data only will provide incoherent results. An important factor that will rule the data management and handling is the sensor heterogeneity and varying sampling rates. Data handling requires managing the system buffer. If a buffer is designed with a certain length, it will not work for higher or lower sampling rates, for example a 250 sample buffer corresponds to 2.5 sec with 100Hz but it can be less or more with lower or higher sampling rates. This introduced an extra overhead for data handling to accommodate elastic buffers to satisfy both the application and smartphone environment requirements.

3.3.3. Infrastructure monitor manager module

Although the system performs a real-time calculation of the infrastructure maintenance indicators, the raw data contains other useful information that can be extracted using data mining techniques. Collecting this data for further processing is therefore a justified action. The data can be collected at maximum sensor sampling rate or as decided by the application. The collected data are then sent to the cloud, using inexpensive data transfer options such as WiFi.

From the engineering point of view, signals carry both useful and unwanted information. The distinction between useful and unwanted information is often subjective as well as objective. Hence signal processing tends to be application dependent [72].

Signal processing techniques allow to extract or enhance useful informa-

Figure 3.6: Framing a 10 second signal into 3 second windows with a $\frac{1}{3}$ d overlap

tion from a stream of adverse information. Altogether, signal processing can be described as an operation designed for extracting, enhancing, storing, and transmitting useful information. Inertial signals collected inside a running vehicle can be inspected by first analyzing the cause of vibration. To this end, Infrastructure monitoring module is composed by two submodules:

1. Data processing & functionalities
2. Services

3.3.4. Data processing module

Considering that measuring each specific infrastructure segment will result in huge amount of sensor data with considerable redundant information, it is more appropriate to compute derived values representing valuable information. To this end, feature extraction is a method to reduce dimensionality of a dataset. One should note that sensor data is streaming and arrives every dt . However the statistical methods require availability of the entire data to be able to calculate valuable information. These reasons motivate us to use feature extraction techniques.

For the purpose of feature extraction, we frame the signal into windows containing only finite length part of the signal. In order to avoid situations in which the signal is framed exactly at the point of interest (occurrence of a relevant monitoring event) and consequently losing the full information about that precise event, we allow the frames to overlap with each other. Figure 3.6 shows a 10 second signal representing a pothole event at the 5_{th} second. After framing the signal, we calculate the features related to the pothole event based on data from the window $W4$ and $W5$. If the frames do not overlap (for instance framing the signal into $W3$ and $W6$), one can see that the information about the pothole is only partially available, leading to missing part of information about properties of the event.

Each window can be described as a feature vector and the entire signal as a feature matrix.

Consider a signal S framed with n window w with a length of m data points d . From each window a set of k features f are extracted, resulting in a feature vector V for each window of the form:

$$V_n = (f_1^n, f_2^n, \dots, f_k^n) \quad (3.6)$$

The whole signal S than can be represented as feature matrix M of the form:

$$M = \begin{bmatrix} f_1^1 & f_2^1 & \dots & f_k^1 \\ f_1^2 & f_2^2 & \dots & f_k^2 \\ \dots & \dots & \dots & \dots \\ f_1^{n-1} & f_2^{n-1} & \dots & f_k^{n-1} \\ f_1^n & f_2^n & \dots & f_k^n \end{bmatrix} \quad (3.7)$$

Feature library

We provide a library of reference features to be used for extracting features based on the context scenario of the infrastructure to be monitored. The library consists of the following features:

- Mean, is the average value of the sample set or statistically the expected values of the measured central tendency.
- Median Absolute Deviation (MAD) The median deviation is a measure of scale based on the median of the absolute deviations from the median of the distribution. The median deviation compared to standard deviation is less efficient as a measure of scale for normal distributions, but more robust for distributions with heavier tails [73].
- RootMeanSquare (RMS) is the mean of the squared values of the sample set.
- Variance (VAR), which is defined as the mean of the squared deviations of a set of numbers about their mean. As with other summary statistics that rely equally on all the numbers in the set, the variance can be severely affected by extreme scores [73].
- Standard deviation (SD), which is a measure of spread or dispersion. It is defined as the (positive) square root of the variance. The SD is a way of putting the mean of a dataset in context and also facilitates comparison of the distributions of several samples by showing their relative spread [73].
- Energy (L2-norm) calculated based on the total size or length of all vectors in a vector space.
- Skewness, which is a measure of symmetry, or more precisely, the lack of symmetry. A distribution, or data set, is symmetric if it looks the same to the left and right of the center point. The skewness for a normal distribution is zero, negative values for the skewness indicate data that are skewed left and positive values for the skewness indicate data that are skewed right [74].

Figure 3.7: A contour plot of normalized features for 7 windows of the signal in Figure 3.6

- Kurtosis, which is a measure of whether the data are heavy-tailed or light-tailed relative to a normal distribution, data sets with high kurtosis tend to have heavy tails, or outliers. The kurtosis for a standard normal distribution is three [74].
- Peak2Peak calculates the difference between the maximum and minimum values of the signal.
- Peak2RMS calculates the ratio of the signal's largest absolute value to the root-mean-square (RMS) value of signal.

For example when the above normalized features are calculated for the 7 windows of the signal in Figure 3.6, can be observed that the anomalous windows **W4** and **W5** are prominent through the feature set as shown in Figure 3.7.

Signal transformation

Since every vibration is caused by a specific wavelength, being that a spinning component on the vehicle or a vertical displacement on the infrastructure, it makes sense to use a transform-based signal processing method [75].

The idea behind transform-based signal processing is to represent the signal as a composite of underlying signals such as sinusoid or wavelet. This form of decomposition of complex signals into elementary ones allows a simpler interpretation and analysis. This category of transform-based signal processing includes the following transform methods that decomposes a function of time into the frequencies that make it up:

- Fourier transform
- Wavelet transformation
- Hilbert-Huang transform

Fourier transform

Fourier transform is a widely used analytic method for signal frequency analysis in particular for vibration analysis. For the Fourier transform, the base functions are the complex oscillations $b_\omega := \exp(i\omega t)$, where t is the time axis and ω is the single frequency parameter that determines the basis function in the family.

$$Fx(t)(\omega) = \langle b(\omega, t), s(t) \rangle = \int_{-\infty}^{\infty} \exp(-i\omega\tau) s(\tau) d\tau \quad (3.8)$$

The drawback of the Fourier transform is the loss of the time information of the transformed non-stationary transient signal.

Short Time Fourier Transform (STFT) overcomes this drawback by windowing the signal into short-enough segments to be considered stationary. However, not all the signals are stationary. A signal is considered non-stationary when its frequency or spectral content change with respect to time. The base function becomes $b_\omega := w(t - t_0)\exp(i\omega t)$, where $w(t)$ is the window function that vanishes outside some intervals and (ω, t_0) is the time-frequency coordinates of the base function in the family, making the inner product in the form of:

$$STFTx(t)(\omega, t_0) = \int_{-\infty}^{\infty} w(\tau) * \exp(-i\omega\tau) s(\tau) d\tau \quad (3.9)$$

Thus, STFT can outline the signal into a function of frequency and time. The result of this transform can also be regarded as a filter-bank with band-pass filters that have the Fourier transform as the window $w(t)$ as frequency response, but shifted to the center frequency ω . All filters therefore have the same bandwidth.

Although the STFT resolves the time frequency resolution, still actual trade-off between time and frequency is determined by the choice of the window function. With regard to the profile lengths, the frequency of the wavelength is proportional to the velocity, meaning that the resolution will not be constant throughout the analysis. Thus, this makes the window size decision a challenging task.

Wavelet transform

Wavelet transform is a multi-resolution transform where a signal is decomposed and described as a combination of elementary waves called wavelets of different duration. The basis function of the wavelet transform is basically the coefficients of the contractions and dilutions of the wavelet. Thus, this allows non-stationary events of various duration in a signal to be identified and analyzed. This is quite important considering that non-stationary events of the same category in a infrastructure signal varies in time corresponding to the speed of travel.

Recovering the signal only from the waveform related to the infrastructure geometry requires the implementation of signal decomposition methods

capable of providing a time frequency representation of the signal. The frequency representation is obtained through transformation of the time series signal. The output of this transform is the inner product of a family of basis functions with the signal.

The wavelet transform resolves the constant bandwidth constraint by adapting the window size to the frequency. This happens in a specific scale invariant way that does not even need the complex modulation anymore. The generic base function becomes a wavelet that is localized and oscillates and it also has zero mean (i.e. the integral over the complete space is 0) [76]. When the wavelet scales in time, the oscillation frequency changes as well. This leads to controlling the localization and oscillation with a single parameter that links them both. The family of base functions becomes,

$$b(\sigma, t_0)(t) = w\left(\frac{t - t_0}{\sigma}\right) \quad (3.10)$$

where w is the original wavelet and σ is the scale parameter. The inner product becomes:

$$Ws(t)(\sigma, t_0) = \int_{-\infty}^{\infty} w\left(\frac{t - t_0}{\sigma}\right) * s(t) dt \quad (3.11)$$

The transformation provides a two dimensionally parametrized result that can also be seen as a filter bank. However, the bandwidth of the filter is proportional to the center frequency of the bands. The time-frequency plane is therefore partitioned non-uniformly.

The Discrete Wavelet Transform (DWT) analyzes the signal at different frequency bands with different resolutions by decomposing the signal into a coarse approximation and detail information. DWT employs two sets of functions, i.e., (i) scaling functions and (ii) wavelet function, which are associated with low pass and high pass filters, respectively. The decomposition of the signal into different frequency bands is simply obtained by successive high pass and low pass filtering of the time domain signal.

The original signal $s(t)$ is first passed through a halfband high pass filter $g(t)$ and a low pass filter $h(t)$. This is shown in Figure 3.8. After filtering, half of the samples can be eliminated according to the Nyquist rule, since the signal now has the highest frequency of $\frac{\pi}{2}$ radians instead of π . The signal can therefore be sub-sampled by 2, simply by omitting every other sample.

Figure 3.8: Discrete Wavelet Transform and subband coding algorithm

Hilbert-Huang transform

Hilbert-Huang transform is another method for time-frequency analysis, the empirical mode decomposition-Hilbert-Huang transform (EMD-HHT), is applicable to both nonstationary and nonlinear signals. EMD-HHT method requires two steps in analyzing the data. The first step is to decompose time series data into a number of intrinsic mode functions (IMF), The second step is to apply the Hilbert transform to the decomposed IMFs and construct the energy-frequency-time distribution, designated as the Hilbert spectrum. The presentation of the final results of the time-frequency analysis is similar to the wavelet transform method, which is a spectrogram. In HHT the decomposition of a time series $H(t)$ into IMF is achieved by extracting the upper envelope of the local maximas and the lower envelope of the local minima. The mean of the envelopes is designated as $m_1(t)$. Extracting the mean from the $H(t)$ results in the first component $h_1(t)$. This procedure can be repeated k times, until $h_k(t)$ is an IMF, thus $h_k(t) = c_1(t)$. $c_1(t)$ contains the shortest period component of the signal as all the low frequency components represented by the extracted envelope are removed. The $c_1(t)$ is removed from $H(t)$ and the process is repeated with the residue $r_1(t)$. This process continues as long as either the $c_n(t)$ or $r_n(t)$ become smaller than a predetermined value or the residue $r_n(t)$ becomes a monotonic function with no extractable IMF [77].

$$H(t) = \sum_{i=1}^n c_i(t) + r_n(t) \quad (3.12)$$

The generated IMFs are transformed by applying the Hilbert transform by finding the real conjugate $y(t)$ of any real $c(t)$ as shown in the equation:

$$y_n(t) = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{c_n(\tau)}{t - \tau} d\tau \quad (3.13)$$

Both c_t and $y(t)$ form a complex conjugate pair $z(t)$ of the form:

$$z_n(t) = c_n(t) + iy_n(t) = a_n(t)e^{j\theta_n(t)} \quad (3.14)$$

From here the amplitude $a_n(t)$ and phase function $\theta_n(t)$ can be calculated as:

$$\begin{aligned} a(t) &= [c_n^2(t) + y_n^2(t)]^{\frac{1}{2}} \\ \theta(t) &= \arctan \left[\frac{y_n(t)}{c_n(t)} \right] \end{aligned} \quad (3.15)$$

The instantaneous frequency is then defined as:

$$\omega = \frac{d\theta(t)}{dt} \quad (3.16)$$

Summary

Considering the properties of the signals measured on the infrastructure being linear non-stationary signals and the aforementioned properties of these signal transformation methods, we chose the Stationary Wavelet Transformation (SWT) for the signal processing service of the system. However, certain properties such the envelope extraction are also offered as part of the signal processing service and will be further discussed in Chapter 5.

The service allows to analyse the signal by choosing the decomposition levels to reconstruct the signal only on certain frequency bands and extract the statistical features for each signal partition.

3.3.5. Aggregation module

Compared to the dedicated sensors of traditional (high-end) measurement vehicles used for infrastructure monitoring, the accuracy of measurements of the smartphones are much lower. However, this inaccuracy can be compensated by the large number of repetitive measurements made on a daily basis by large number of active participants. This will guarantee the required spatial and temporal resolution required for determining the infrastructure state.

The aggregation module addresses the following challenges posed by the crowd-sourced nature of measurements:

- Sparse and uncoordinated measurements: smartphone owners measure infrastructure segments randomly without having a priori knowledge about the track being measured.

- Heterogeneity of measurement devices: different types of smartphones with different sampling rates, processing power, operating systems, and sensor accuracy will be used.
- Unequal spatial and temporal resolutions: temporal and spatial frequencies of sampling will be different and vehicular speed and GPS inaccuracy will increase the latency.

To achieve the required accuracy in both space and time, computational geometry method such as the Voronoi Diagrams or the Delaunay Triangulation (*DT*) can be used. Pairing all measured segments together and updating the segment position with new contributions makes the map-matching process accurate and efficient.

Map-matching challenge consists of combining huge amount of streaming data from the smartphones in space and time and translating the uncertain GPS measurements into an exact geographical location of transport infrastructure segment.

The module also addresses the problem of spatio-temporal data measurements, proposing a time-machine approach, in which the evolution of the infrastructure segment state is updated using a weighted function that dilute previous measurements and weight up the new ones, yielding an accurate time resolution state.

3.3.6. Data transmission module

This module assists the system to communicate with other smartphones opportunistically, utilizing WiFi and GPRS. Although the system performs a real-time calculation of the infrastructure maintenance indicators, the raw data contains other useful information that can be extracted using data mining techniques. Collecting this data for further processing is therefore a justified action. The data can be collected at maximum sensor sampling rate or as decided by the application. The collected data are then sent to the cloud, using inexpensive data transfer options such as WiFi.

Data connectivity requirements

Data connectivity is a fundamental requirement for crowd sensing-based systems, as the paradigm is based on in-situ contribution of individuals. Due to the fact that for each segment of the transport infrastructure, only the geo-location (coordinates) and the computed maintenance indicators need to be transmitted, a wide bandwidth communication channel is not needed.

However, from a big data perspective, transmission and availability of other intermediary computations or the raw sensed data may be beneficial for further analysis. Therefore, availability of different types of data transmission may facilitate and reduce transmission bottlenecks. Modern smartphones provide mobile network data connectivity (via GPRS) as well as WiFi and Bluetooth, which can be exploited for use in transport infrastructure monitoring.

Cooperative opportunistic data dissemination

An opportunistic vehicle to vehicle network facilitates an increase in accuracy for the anomaly detection service by collaborating and exchanging information regarding transport infrastructure indicators and features without requiring the smartphones to communicate with a central cloud service. Its execution is prioritized based on severity of anomaly being detected by smartphones. The network relies on the communication range of smartphone's WiFi and the WiFi chip switching between the hot-spot mode to disseminate smartphone data and transport infrastructure segment information and the client mode to receive the information utilizing the SSID packet to encode the road information. Given the fact that the SSID length is limited to 32 bytes only, the data packets need to be encoded in such a way that it encloses all important information such the location, type, number, and nature of the infrastructure anomalies a given road length of are radius.

3.4. Summary

In this chapter, we have presented requirements and architecture of our crowd sensing-based infrastructure monitoring system. The system relies on the sensing, communication, and processing capabilities of the modern smartphones as well as sophisticated data processing, classification and clustering algorithms. The processing scheme of the system can be implemented on top of the smartphone OS allowing a wide range of deployment. The system architecture encapsulated required modules and components to support and monitor different infrastructure types, their associated geometry indicators, users, authorities and responsible engineers. Short description of principles and concepts of these modules presented in this chapter will be followed with details description of our designed methods and algorithms to instantiate the components in the upcoming chapters.

4

Map-matching and aggregation

This chapter presents an important aspect of crowd-source based transport infrastructure monitoring, the map matching and aggregation of huge amount of sparse location data recorded by the smartphone with the location of the infrastructure. To achieve the required accuracy in both space and time, the algorithm will use a computational geometry method, namely the Delaunay Triangulation (DT), and combines its properties to efficiently solve the nearest neighbour searching problem. Pairing all measured segments together and updating the segment position with new contributions makes the map-matching process accurate and efficient. The algorithm also addresses the problem of spatio-temporal data measurements, proposing a time-machine approach, in which the evolution of the infrastructure segment state is updated using a weighted function that dilute previous measurements and weight up the new ones, yielding an accurate time resolution state.

4.1. Crowd-source localization challenges

Continuous monitoring of transport infrastructures using crowd-sensing is a new concept being inspired by the power of active participation and contribution of the general public in provision of real-time measurement data about infrastructure characteristic.

Compared to the dedicated sensors of traditional measurement devices used for infrastructure monitoring, the accuracy of measurements of the smartphones are much lower. However, this inaccuracy can be compensated by the

This chapter is based on:

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large number of repetitive measurements made on a daily basis by large number of active participants. This will guarantee the required spatial and temporal resolution required for determining the infrastructure state.

It is well-known that smartphones GPS suffers from inaccuracy and latency, causing substantial uncertainties regarding the exact location of the pathway segment. This is particularly important for monitoring dense infrastructure networks such as city center road networks, multi-lane highways, and railroad switching tracks. Although GPS localization has become more accurate during the recent years, it still has an accuracy of more than 7m on smartphones [78]. We have experimentally derived an RMSE (root mean square error) of 8.5m for the GPS position of an stationary phone, while the standard deviation of the sampling latency was in the range of 0.05ms. The GPS chips of smartphones have a GPS sampling rate of 1Hz, i.e., 1 sample/second. Considering the fact that vehicles travel with a variable speed ranging from 8.3 - 33.33 m s⁻¹, failure of the device report one sample will lead to a 2 second delay between samples and the distance traveled in a range of 16-66 m.

To cope with this problem, we present an algorithm for map-matching of crowd-sourced measurements for monitoring ground transportation infrastructures. Map - matching challenge consists of combining huge amount of streaming data from the smartphones in space and time and translating the uncertain GPS measurements into an exact geographical location of transport infrastructure segment. The algorithm addresses the following challenges posed by crowd-sourced nature of measurements:

- Sparse and uncoordinated measurements: smartphone owners measure infrastructure segments randomly without having *a priori* knowledge about the track being measured.
- Heterogeneity of measurement devices: different types of smartphones with different sampling rates, processing power, operating systems, and sensor accuracy will be used.
- Unequal spatial and temporal resolutions: temporal and spatial frequencies of sampling will be different and vehicular speed and GPS inaccuracy will increase the latency.

The rest of the chapter is organized as follows. We provide a short overview of related work in the domain of GPS data aggregation and visualization for transport infrastructure monitoring. In Section 4.3, we describe the problem of point location with *DT* and nearest neighbour search and we present our map-matching algorithm for aggregation and visualization of large amount of inaccurate GPS data being collected by smartphones. In Section 4.4, we present our evaluation of the proposed algorithm using crowd-sourced data collected from smartphones in trains, cars, and bicycles.

4.2. Related work

Use of crowd sensing concept for road anomaly detection with various degree of success, mostly for potholes and bumps, has been reported in a number of publications, for example [34][37][36][79]. These papers also present certain methods for data aggregation and visualization, mostly based on clustering algorithms to cluster the detected anomalies. However, none of them address the temporal nature of road surface anomalies, i.e., the fact that they change in time either due to further degradation or due to swift improvement when being repaired.

In [34], a cluster is created by creating a grid of distances between all reported locations and averaging the center of the cluster. This approach is similar to the $k - \text{mean}$ clustering method and does not take into consideration the scalability issues being introduced by huge distance grids and updating or splitting the cluster. We propose an improved clustering algorithm in Chapter 5, where the detected anomaly is enhanced through driver behavior analysis approaching the anomaly. The proposed clustering algorithm takes into consideration the swerve of the vehicle before and after approaching the anomaly and updates the cluster accordingly. A new clustering algorithm for processing GPS-based road anomaly is reported in [80] and uses a Mahalanobis distance. The proposed clustering algorithm considers the evolving nature of road anomalies and adapts the cluster accordingly. By weighing the cluster based on both the measurements and time of measurements, the algorithm promotes a set of anomalies into a cluster or deletes the cluster if no anomalies are reported inferring that the anomaly is repaired. This method does not consider the driver behavior aspect. Moreover, the number of measurements can also decrease depending on the driving habit of the drivers as shown in [65].

Despite the fact that authors of [52][81] describing RoadRoid mentioned data aggregation and visualization, no detailed explanation about the methods used have been reported. Their platform performs map-matching using geometries from OpenStreetMap and Swedish national road data-base (NVDB) [81]. It is worth to mention that RoadRoid cannot calculate attributes such as road width and number of lanes. SmartRoadSense (SRS) [56] is an Android application that calculates the Power Spectral Density of the road elevation profile. The accelerometer data is collected at a sampling rate of 100Hz. The roughness calculation is conducted on windows of 100 samples, corresponding to the GPS sampling rate. Authors offer a model, in which the Power Spectral Density is calculated by filtering the dampening effect of the tires and suspensions and other stationary noise using Linear Predictive Coding (LPC). Authors of [82] describe a method called SRS for data aggregation and reduction. The method is implemented in the cloud in 3 phases, i.e., (i) collection of measurements based on their geo-locations, (ii) computation of a temporal aggregation of the points using means of weighing the freshly received reports, thus keeping the database updated with latest significant changes of the infrastructure, and (iii) visualization using a graphical map with color-coded points corresponding to the calculated roughness. In a successive work [83], SRS aggregation is further

improved by introducing an algorithm for phase one. The algorithm deals with the uncertainties of GPS location on dense road networks, road joints, diverging roads and crossroads. It does so by comparing the location of three consecutive points and correcting the middle point location based on the distance from two adjacent ones and matching them to the road geo-location using Open Street Map. They report that SmartRoadSense cannot distinguish between lanes or directions as there is only one index per road segment.

Figure 4.1: A mock up of different road scenarios, with joints, crossing, multiple and single lanes, representing the infrastructure with Delaunay triangles. Notice the red vertices represent the lane. For each new measurement the GPS point will fall inside or on the vertices of the triangle, making the task of point localization and measurement aggregation trivial.

4.3. Aggregation and visualization of large data sets

The traffic infrastructure inventory consists of the following items: roads, railways, junctions, crossing points, bridges, etc. These items are further divided into subsets of lanes per road and tracks per railroad. Furthermore they are divided into segment profiles of certain length, for instance the road hectometer segments. Following this hierarchical relational model, the monitoring companies measure the state of the infrastructure and report the results to the property owner. For example, every 10 km two-lane road segment is split into 100 hectometer per lane segments for a total of 200 segments. A crowd-sensing approach used to monitor the above mentioned road with only 2 vehicles per day will generate 146,000 segments per year. Considering a real world scenario like for The Netherlands which has 139 thousand km of road network, the chal-

length of processing, aggregating, and visualizing such a large amount of data becomes clear very quickly. Figure 4.1 shows a typical road network consisting of different roads with different number of lanes. The dots represent the profile edges. Usually the traffic is concentrated on the right lanes of the road, where the most-right lane is used by heavy trucks. Therefore, the most-right lanes deteriorate faster than the left ones. This implies that the lane should be precisely reported while monitoring multi-lane roads. Achieving this accuracy with smartphone measurements requires a fast and reliable algorithm to sort the segments based on their closest location to the hectometer stone. For doing so, we use the nearest neighbour search based on Delaunay triangulation [84] method.

Figure 4.2: a) Delaunay triangle properties. Updating the DT by splitting the triangle when b) point falls inside the triangle, c) when point fall on the vertex

Geometric proximity problems, or the closest point problems, have always been a popular topic in computational geometry [85][84]. These problems deal with distances in sets in $\mathbb{R}^D$. Let us consider a set of initial GPS fixes denoted by $P = \{p_1, p_2, \dots, p_n\}$ spaced approximately with a distance of 10m, received from a vehicle traveling on an unknown road. The set P will serve as the indication of every road connecting point p_1 to p_n . Let us also consider another vehicle passing through this road providing a GPS fix set denoted by $Q = \{q_1, q_2, \dots, q_n\}$. To aggregate the GPS fixes of both vehicles, we need to pair the GPS points within a certain range into a single point.

One method to do so is to create a mesh-grid of distances between all points into a matrix $D(n \times n)$ to find the minimum distance for each pair. Since there are $\binom{n}{2}$ pairs of distinct points and the distance between two points can be computed in $O(D) = O(1)$ time, the problem can be solved in $O(n^2)$ time. This method is computationally expensive and does not scale well if the path from

Q splits or goes beyond P .

The DT on the other hand can be used for the set P to create a mesh of points connected together in such a way that they create a set of triangles with certain properties [85]: Let us assume P to be a set of points in the plane. Then (i) three points denoted by $p_i, p_j, p_k \in P$ are vertices of the same face of the Delaunay graph of P if and only if the circle through p_i, p_j, p_k contains no point of P in its interior, (ii) two points $p_i, p_j \in P$ form an edge of the Delaunay graph of P if and only if there is a closed circle C that contains p_i and p_j on its boundary and does not contain any other point of P .

Let $\mathcal{T}$ be the triangulation of P . Then $\mathcal{T}$ is a DT of P if and only if the circumcircle of any triangle of $\mathcal{T}$ does not contain a point of P in its interior. A triangulation $\mathcal{T}$ of P is legal if and only if $\mathcal{T}$ is a DT of P , Figure 4.2.

4

Figure 4.3: Delaunay triangulation and closest point problem. In dotted red are the new triangles that will form from the new points not close enough to the existing points.

Any angle-optimal triangulation of P is a DT of P . Furthermore, any DT of P maximizes the minimum angle over all triangulations of P . Every new edge created in DT or in legalize edge during the insertion of p_r is an edge of the Delaunay graph of $\{p_{-2}, p_{-1}, p_0, \dots, p_r\}$. The DT of a set P of n points in the plane can be computed in $O(n \log n)$ expected time, using $O(n)$ expected storage. If the point q_m falls outside the convex hull and therefore does not belong to any triangle, the new point will be included into the triangulation by creating a new triangle and rearranging the boards of the convex hull, as shown in Figure 4.3.

Figure 4.1 illustrates the road section with the segment edges triangulated creating Delaunay triangles. The triangle vertexes in red correspond to the road segment profiles.

One should note that for this problem, we use the Haversine distance [86] instead of the Euclidean distance since the distance is the great-circle distance.

The Haversine distance can be expressed as:

$$d = 2R \arcsin \sqrt{\sin^2\left(\frac{\varphi_2 - \varphi_1}{2}\right) + \cos(\varphi_1)\cos(\varphi_2)\sin^2\left(\frac{\lambda_2 - \lambda_1}{2}\right)} \quad (4.1)$$

where R is the Earth radius and (φ, λ) are the corresponding latitude and longitude coordinates of the points.

4.3.1. Map creation and map-matching

In real world scenarios, an initial database of road profiles is not always available. For that matter the application may also lack a road database relying only on online map providers like Google Maps or Open Street Map (OSM).

Let us consider a vehicle traveling through an unknown road. The GPS receiver of the smartphone will create a set of points P corresponding to the road with an estimation error ξ . Figure 4.4 shows some examples for multiple GPS fixes over different stretches of road with different geometries. Figure 4.4.a.b.c shows one-lane road while Figure 4.4.d.e shows two-lane roads in city Enschede in the Netherlands in both directions. The accuracy of the GPS is sufficient to distinguish bridge gaps, road widening, roundabouts. Online map providers can provide a geometry of the closest road to the point set P . Adopting that information, the travel direction can be estimated. We aim to create an initial DT for the point set P . For every new trace P' over that road, we always update the position of points with every new P' set. For each updated point, we check if the updated triangle $\mathcal{T}$ is a true Delaunay triangulation. If not, the affected triangles will be modified. This procedure will be repeated until a stable lower bound for the point locations is found. Algorithm 6.1 shows our approach and the steps to be followed:

4.4. Performance evaluation

We evaluate our map-matching approach using various data-sets collected by smartphones for the purpose of ground infrastructure monitoring. All GPS fixes collected by smartphones have the sampling rate of 1Hz. Table 4.1 summarises our experimental setups showing different infrastructure pathways used to conduct the measurements. The ground truth for our performance evaluation was collected by special measurement vehicles, i.e., UFM120 and ARAN.

UFM120 is a track geometry measurement train and ARAN is an automatic road analyzer van. Smartphones were also placed inside these vehicles while conducting the measurements. The evaluation process consists of comparing the GPS fixes calculated by our algorithm with the ground truth collected by UFM120 and ARAN. Beside the accurate GPS position of the experimental track, UFM120 and ARAN also provide the accurate infrastructure inventory for the tracks, i.e., all segment profile coordinates.

The bike ground truth is set by retrieving Google road coordinates and map-matching. Because Google maps do not provide any information about the

Table 4.1: Experimental setup inventory

Trip Nr	Start	Stop	Length	Vehicle	SPhone
Train					
1	Amersfoort	Utrecht	18.6km	UMF120	4xM,4xS
2	Utrecht	Hogebrug	24.3km	UMF120	4xM,4xS
3	Utrecht	Leiden	48.8km	UMF120	4xM,4xS
4	Leiden	Utrecht	48.8km	UMF120	4xM,4xS
5	Enschede	Zwolle	63.4km	NS DM90	S
6	Enschede	The Hague	192km	NS VIRM	2xS
7	Enschede	Schiphol	163km	NS ICM	S
Cars					
1	Deurninger	Enschede	8.5km	ARAN	S
2	Deurninger	Enschede	3x8.5km	Mazda CX5	M,2S
3	Deurninger	Enschede	40x8.5km	Audi A4 coupe	M,S
4	Deurninger	Enschede	2x8.5km	Citroen C4	M,O
5	UT campus		15x18km	Citroen C4	M,S
Bikes					
1	Enschede(urban)		152.16km	Bike1	M
2	Urban,Forest,Highspeed		221.67km	Bike2	S
3	Urban		253.15km	Bike3	S
4	UT campus		47.43km	Bike4	S

Figure 4.4: GPS fixes for a road in both directions, notice how in a),b) and c) the directions are well distinguished even the bridges and roundabouts. d) and e) show traces for one lane roads.

Algorithm 4.1: Road segment aggregation

```

1: function MAPMATCHING ( $P$ )
2:   CREATEROADPROFILESEGMENT ( $P$ )
3:   CREATETRIANGULATION ( $\tau$ )
4: end function

5: function CREATEROADPROFILESEGMENT ( $P$ )
6:   return Road profile segment set  $RS$ 
7: end function

8: function UPDATETRIANGULATION ( $P'$ )
9:   return Road profile segment set  $RS$ 
10: end function

11: function UPDATEPOINTS ( $P', DT$ )
12:   return Road profile segment set  $RS$ 
13: end function

14: function CHECKNEARESTPOINTLOCATION ( $P, DT$ )
15:   if  $DT$  which has  $P_n$  inside then
16:     return  $DT$ ;
17:   else UPDATETRIANGULATION ( $P$ )
18:   end if
19: end function

20: function MAIN( $P$ )
21:   if  $DT$  not exists then
22:     create  $DT$ ;
23:   else
24:     CHECKNEARESTPOINTLOCATION ( $P, DT$ );
25:     UPDATEPOINTS ( $P, DT$ )
26:     if  $Diff(updated, previous) > D_{threshold}$  then
27:       UpdateDone;
28:     end if
29:   end if
30: end function

```

width of the road, the evaluation is conducted under the assumption that Google roads coordinates correspond to the middle of the road segment. Therefore, half of the road width is subtracted from the estimated distance.

Figure 4.7 shows the results of our aggregation method and visualization of the GPS fixes measured on the road and the rail road tracks. In what follows, we present the numerical comparison of these results.

4.4.1. Re-construction of road geometry

We re-construct the geometry of the road used for our experiment using multiple consecutive measurements made by different drivers. The first GPS fixes serve as the initial Delaunay triangulation template. By iterating through Algorithm 4.1, we updated that template to achieve more accurate results. The aim of the experiment is to identify the necessary number of GPS fixes for an accurate geometry re-generation. For each update all the template profiles are compared with the ground truth GPS fix from ARAN. Figure 4.6.a shows a box-plot illustrating the distance between the aggregated GPS fixes using our approach and those collected by the ARAN for each iteration. One can observe that aggregating 50 GPS fixes is enough to re-constructing the road geometry accurately. It worth mentioning that ARAN GPS fixes may not correspond to the middle of the lane. Therefore, we consider the template to be correct and accurate within a distance range of 1.5 m. For roads with multi-lane on the same direction, a prior information on the number of lanes can be combined with the driver behavior algorithm [65] to detect the lane changes. However, the lane information is not available neither by the Google Maps nor OSM.

Figure 4.5 shows the road roughness measurements conducted with the Citroen C4 in the University of Twente Campus. Seven trips driving through 18km of roads in and around the campus were measured with the mobile phones attached on the windshield. Figure 4.5.a shows the all the profiles from 15 measurements. After the data aggregation the number of points is reduced to the single profile segment. Most of the roads in campus have one lane with bike paths on both edges, therefor one point per profile, whereas on wider roads 2 parallel profiles are created.

Figure 4.5: University of Twente Campus IRI calculation a) 15 independent measurements, b) IRI aggregation from 15 measurements

Figure 4.6: The improvement of distance every each trip, a) road Delaunay triangulation template using data from the Audi A4 car. The distance comparison is made with ARAN GPS trace, b) rail road Delaunay triangulation template, and c) bike path Delaunay triangulation template

Figure 4.7: Results of aggregated GPS fixes for roads a),b) and railroads c).

4.4.2. Re-construction of railroad track geometry

For the railroad track geometry evaluation, compare the GPS fixes of 8 smartphones placed inside the UFM120 in the same manner as in the road case described above. The smartphones were placed in both sides of the train near the windows. An important aspect to mention in the case of trains is the weak reception of GPS signal limited by the line of sight between the smartphone and the GPS satellites. Trains carriages have an all metal frame with windows orthogonal to the floor, which can significantly impact the GPS accuracy. Therefore, all the independent smartphone GPS fixes exhibited a larger error but also an important feature, they show on which side of the train the smartphone was placed. The smartphones placed on the left side tended to report the point location on the left of the tracks and *vice versa* for the ones placed on the right side. However, after aggregating all the fixes, an accuracy in order of 1.5 meter is obtained as shown in the graph Figure 4.6. Figure 4.6.b shows a boxplot of aggregating data distance between the template and UFM120 GPS for each iteration by adding the GPS fixes of consecutive smartphones.

4.4.3. Re-construction of bike path geometry

It can be seen from Figure 4.6.c that Delaunay triangulation templates created using data from the first bike trips are closer to the ground truth. As trips became more random, the average accuracy became more persistent towards the ones observed in measurements about the road and rail roads. One should note that the bike paths in the Netherlands are not always dedicated paths, some roads allow bicycles to drive at the edges of the road. As such, when both bike and car GPS fixes are aggregated some discrepancies on the lane position can be observed. Therefore, we aggregate the measurements made on the bike path using a separate Delaunay triangulation template.

4.5. Summary

In this chapter, we presented an algorithm for aggregation and visualization of enormous amount of GPS fixes collected through crowd-sensing for continuous monitoring of transport infrastructures.

The algorithm uses Delaunay triangulation to efficiently resolve the problem of point location and nearest neighbour for a huge amount of streaming geo-spatial data. The algorithm reduces the amount of data (i.e., number of GPS fixes) and increases the accuracy of the transport infrastructure asset location up to 1.5m regardless of vehicle, smartphone or infrastructure type.

Performance evaluation of our technique using data collected by smartphones and the ground truth collected using special measurement vehicles, i.e., UFM120 track geometry train and ARAN Road Analyzer on various infrastructure types and smartphone types shows the very similarity between the two.

5

Road anomaly detection

In this chapter we will discuss and present the principles and techniques behind services related to our crowd sensing-based services for road anomaly detection and driver behavior analysis.

Part of the discussion will focus on our data collection methodology combined with the audio-visual data labeling. A new clustering method is proposed to facilitate the aggregation of the detected anomalies with the detected driver manoeuvres swerving around the anomaly.

5.1. Road anomaly detection

Road anomalies can be characterized as static, all the anomalies that are embedded on the road surface: i) Potholes, ii) Speed bumps, iii) Rail tracks, iv) Manholes, v) etc... Temporal anomalies include all the anomalies that appear temporarily on the road surface: i) Debris, ii) Fallen trees, iii) Dead animals, iv) Driver behavior, v) etc...

All these anomalies will generate excessive vibration with a high energy content. The location of anomaly can be identified by the GPS location at the time of the event. If a driver changes the direction of the car to avoid the anomaly the high energy event will not happen, failing to detect the anomaly. However, the manoeuvre itself can be used as an indicator of the anomaly.

This chapter is partially based on:

"RoADS: A road pavement monitoring system for anomaly detection using smartphones". In: *Big Data Analytics in the Social and Ubiquitous Context. Lecture Notes in Computer Science 9546*, Springer Verlag, Berlin, pp. 128-146.

A smartphone based method to enhance road pavement anomaly detection by analyzing the driver behavior. In: *Adjunct Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2015 ACM International Symposium on Wearable Computers*, pp. 1169-1177.

SpinSafe: An unsupervised smartphone-based wheelchair path monitoring system. In: *Proceedings of the IEEE International Conference on Pervasive Computing and Communication Workshops, PerCom Workshops 2016*, pp. 1-6. IEEE Computer Society.

Thus, both approaches can be used as anomaly indicators. Despite the fact that the road is mostly used by automobiles, other types of wheeled vehicles (e.g. bikes and wheelchairs) with different characteristics and needs make use of the them, too. Not all road anomalies are relevant for automobiles, while they will affect the quality of ride for wheelchairs or bikes. Our road infrastructure monitoring services are encapsulated in a subsystem called RoADS. RoADS enables reactive maintenance by providing anomaly detection capabilities for all types of wheeled vehicles on the road infrastructure and consequently informing road users and authorities about them. While the *a priori* knowledge required for classification of road anomalies differ per vehicle type, the underlying learning and classification techniques in RoADS are the same. Figure 5.1 illustrates the architecture and sequence diagram of our anomaly detection service presented by RoADS.

Figure 5.1: Sequence diagram of RoADS's anomaly detection service

5.1.1. Road pavement anomalies

The road pavement is characterized by an asphalt or concrete layer surface that facilitates the movement of the wheeled vehicles. Every situation where this pavement disrupts the smooth flow of the vehicle traffic is considered an anomaly. Figure 5.2 illustrates different types of road pavement anomalies.

Transversal anomalies include speed humps, speed bumps, road and bridge joints, railroad crossings. Mild anomalies refer to those segments of road where the surface of the road is not even but potholes have not yet been created. They include sunken crocodile cracks, patched roads, tree roots, sunken manholes, raveling (delamination of the sealing layer). Severe anomalies include different types of potholes and severe road deterioration.

5.1.2. Car dynamics

Vehicles are complex dynamic spring-mass systems. When analyzing the effect of anomalies on the vehicle, only the bounce of the vehicle needs to be taken into consideration. This bounce can be measured by measuring the vertical acceleration of the vehicle, among others. However, when a car drives over a road anomaly rotational movements also occurs.

One should recall that all our services rely on crowd sensing data being acquired by smartphones. Figure 5.3 shows the orientation of the phone inside

Figure 5.2: Different types of road pavement anomalies

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the car. All axes will be re-oriented with respect to those of the smartphone. It can be observed that in a vehicle exist two forms of movements, i.e., the translational and the rotational movement.

Figure 5.3: Smartphone orientation inside the vehicle

When driving with a constant speed through a smooth flat road, an accelerometer mounted inside the vehicle should only measure the gravity. Once the vehicle hits an anomaly as shown in Figure 5.4a, the accelerometer should also measure the vehicles lateral Y_a and vertical X_a displacement (, which is equal to the depth of the road anomaly). Also the orientation of the vehicle changes by rotating aside with an ϕ angle. However, if the vehicle drives through a transversal anomaly as shown in Figure 5.4b, the displacement X_a equals the height of the speed hump. In this case, the displacement will be measured only on the vertical axis X of the accelerometer. Moreover, the orientation of the vehicle changes, pitching up with an angle θ . From these, we can infer that measuring the rotational movement of the vehicle can help accuracy of anomaly detection and their classification.

Figure 5.4: The dynamics of the vehicle over side and transversal anomalies.

Figure 5.5: Readings of linear accelerometer axis $|X|$ (green) with speed from GPS (red) and velocity computed from linear acceleration (blue). One may notice the drift accumulated in the segment between two black bars.

5.1.3. Coping with speed dependency

The vehicles are equipped with suspension and dampers to attenuate certain vibrations caused by road anomalies. When a vehicle drives slowly, the RPM (Revolutions Per Minute) of the wheel is low. This results in low vibration input from the road. As the speed increases, the wheel RPM and the frequency of the road input also increases. This results in a vibrating signal as shown in Figure 2.4. We call this phenomenon *speed dependency*. It can be seen from Figure 5.6a that when the speed signal from GPS and the absolute values of accelerometer x-axis are plotted for a flat road, the envelope of accelerometer follows the speed signal from GPS. Figure 5.5 shows that in the segment between vertical dashed lines the vehicle is driving with high speed through a relatively flat highway, but the peaks are much higher in the segment between vertical black bars when the vehicle is driving slower up and down a hill. Velocity theoretically can be estimated by integrating the z-axis of the accelerometer, namely the longitudinal acceleration. Results of this integration can be satisfactory for flat roads, but not for uneven roads. Figure 5.5 shows data from a vehicle climbing up a hill. It can be seen that in the segment between black bars the integrated velocity increases, but not the GPS speed does not. The way speed, slopes, and drift affect inertial sensors has a resemblance with the amplitude modulated signals in radio technology [87]. The accelerom-

eter signal measuring complex mechanical vibrations is modulated with different signals. It acts as a carrier for different signals like speed, slope degree, engine and tire revolutions. Envelope demodulation is often used for empirical

(a) $|X|$, scaled GPS speed and envelope

(b) raw and demodulated X

Figure 5.6: (a) Absolute value of x-axis accelerometer $|X_{acc}|$ plotted against scaled GPS speed and envelope, (b) Demodulated signal dX_{acc} (blue) plotted against raw signal X_{acc} (red).

mode decomposition (EMD) [88] of complex mechanical vibrations in Hilbert-Huang transform [77]. Demodulated signal dS is computed from the raw signal S based on Equation (5.1),

$$dS(t) = \frac{H \circ S(t)}{E \circ |H| \circ X_{acc}(t)} \quad (5.1)$$

, where t is time, $\circ$ is the function composition, E is the moving average filter (expressed in Equation (5.2)), H is the high-pass filter applied to the signal, and X_{acc} is the x-axis accelerometer.

$$E(t_i) = \frac{1}{M} \sum_{j=0}^{M-1} X(t_{i+j}) \quad (5.2)$$

The envelope demodulation does not only represent the speed signal but it also compensates for the slope and other low frequency components. It is clear from Figure 5.7 that the demodulated signal better shows the anomalies. Figure 5.6a shows the signal for the absolute values of the x-axis, the speed, and the envelope. Figure 5.6b shows how the demodulated signal differs from the raw signal.

Figure 5.7: (a,b) 3D spectrogram of raw and demodulated accelerometer signal with plotted x-axis accelerometer (red) on top; (c,d) 3D spectrogram of raw and demodulated gyroscope signal with plotted y-axis (red) and z-axis gyroscope (blue) on top.

5.1.4. Signal analysis

Once the speed dependency is taken care of and removed, the amplitudes generated by the anomalies are more uniform. To detect anomalies the use of a threshold may seem appropriate. However, not all vehicles generate the same amplitude when driving through the same anomaly.

Analyzing the signal in time domain is not enough as the signal is composed of different vibration elements being modulated together. Most of the times, the paths on which the wheeled vehicles ride are not flat and the surface gets more rough as it ages, the tree roots grow, manholes are created, and sunken road pavements make the surface uneven. Frequency domain analysis, which shows the frequency components of the signal, is more suited for narrow band stationary signals.

All the vibrations inside the vehicle happen at a certain frequency bands. The most prominent vibrations on a traveling vehicle are the engine revolutions and the wheel revolutions. A vehicle engine usually operates at a range of 2000 RPM to 3500 RPM or 30 Hz to 50 Hz. When the vehicle is standing still, the engine operates at 1000 RPM or 15 Hz. It is common for the city vehicles of B and C classes that have 14 inch to 15 inch tires and drive in the range of 30 km/h to 90 km/h with wheels spinning at 7 Hz to 23 Hz. The frequency of vibration from road anomalies depends on many factors including radius and

Figure 5.8: SWT decomposition at 4 levels with a sym5 wavelet.

width of the tire, suspension characteristics, and mass of the vehicle.

Road engineers consider road pavement anomalies as longitudinal waves. They all generate vibrations with frequencies depending on the speed of vehicle. Considering the properties of wavelets and their ability to represent the signal in time and frequency, we use the wavelet transformation for signal analysis. They are better suited for analysis of sudden and transient signal changes and analyzing irregular data patterns, such as impulses generated at different time instances. Discrete Wavelet Transform (DWT) uses multi-resolution filter banks and wavelet filters to analyse and synthesise the original signal [89]. It gives frequency resolution in low frequencies and time resolution in high frequencies [90]. Hesami and McManus [91] showed that DWT analysis outperforms power spectral density (PSD) analysis when used to estimate and analyse road roughness.

The Stationary Wavelet Transform (SWT) known also as *algorithme à trous* [92] [93] decomposes sensor signals into 4 levels using Symlet sym4 wavelets. Figure 5.8 shows the plot of the original signal on top and 4 levels of SWT decomposition, the approximations on the left and the details on the right. The high frequencies are visible at the details column d1 and lower frequency signal at a4. Also because we are using SWT we can have a good time resolution for every level of decomposition. We extract the following features from SWT decomposition: absolute mean, standard deviation, variance, energy for every level of detail and approximation.

In situations in which the vehicle is standing still, for example at a parking lot or when the vehicle is waiting for a traffic light or is in a traffic jam, the vibrations are minimal and are mainly due to the sensor noise. For these sce-

narios, the variance of the low frequency signal is close to zero as shown in Figure 5.9. These segments can very well be discarded.

Figure 5.9: Stop segments and the variance of the 4-th level of decomposition

5

5.1.5. Anomaly detection and classification

One of the main concerns of anomaly detection and classification is setting the ground truth and comparing the results with that. The algorithm should detect different types of anomalies. This is a rather challenging task, especially when aiming to implement on smartphone platforms with limited energy consumption and processing power. Based on the availability of the labeled data, anomaly detection techniques can be divided into:

- *Supervised* - when normal and anomalous patterns are learned from a collection of labeled data segments of infrastructure.
- *Semi-supervised* - when training labels are available only for *normal* segments classifying any segment that does not fall into the normal class as anomalous.
- *Unsupervised* - when no a priori knowledge about the type of segments infrastructures in terms of being normal or anomalous is available.

Let us consider that we intend to monitor an infrastructure segment denoted by S . To detect the anomalous parts of the segment, a target function is required such that: $\hat{f} : R \leftarrow \text{good, bad/anomalous}$

The goal of the supervised machine learning is to compute a suitable model for the labeling process that approximates the original process as closely as possible [94]. For this purpose, all *good* parts of the infrastructure segment S being denoted by G (where $G \subset S$) are labeled as good, leaving the remaining parts as *bad / anomalous*.

$$G = \{x, y | x \in S \text{ and } y = f(x)\}.$$

The aim is to use D and compute a function:

$\hat{f} : R \leftarrow \{\text{good, bad/anomalous}\}$ for all $x \in R$ that:

$$\hat{f}(x) \cong f(x) \quad (5.3)$$

The goal of unsupervised machine learning is to compute a suitable model from a collection of observations $\{s_1, s_2, \dots, s_n\}$ sampled from a distribution $p(S)$ to describe the properties of $p(S)$.

Our anomaly detection service is based on a set of pre-processing and transformation steps aiming to translate sensor data of smartphones into distinctive features representing characteristics relevant to frequently occurring anomalies.

We will use both supervised and unsupervised machine learning techniques for the purpose of anomaly detection and infrastructure segment classification.

Support Vector Machines (SVM), is an supervised learning algorithm that computes a set of hyperplane $\{h_1, h_2, \dots, h_n\} \subset \mathcal{H}$ and finds the hyperplane that has the largest distance (functional margin) to the nearest points on any class. Our SVM-based technique first detects the anomalies on the infrastructure segment and consequently classifies them into three distinctive transversal, mild, and severe anomaly classes.

Considering the diversity of anomalies and types of transport infrastructures it is not always feasible to label the data or the anomaly types are simply unknown. We use a unsupervised learning algorithm to build classification models. To do so, we use the Self Organizing Map (SOM) [95], which based on Artificial Neural Network (ANN). The idea behind SOM is to cause different parts of the network to respond similarly to certain input patterns. This is partly motivated by how visual, auditory or other sensory information is handled in separate parts of the cerebral cortex in the human brain [96]. Our technique allows the creation of segments clusters that exhibit similar attributes. This is particularly important to create state hierarchies of segment infrastructure and monitor their metamorphosis into other categories. For instance, mild potholes if left alone, in time can transform into bigger severe potholes, thus the corresponding infrastructure segment will classify accordingly.

Supervised learning

The process consists of training algorithm to build a model with a set of training data and assign the new data to one of the known classes. All data can be represented as distinctive features extracted from the original data. This features can be mapped in space in a way that can be divided into classes. We use the Support Vector Machines (SVM) for our supervised learning phase. SVM is an algorithm that increases the separable gap between different classes as wide as possible considering the margins of the class as support for the gap. SVM assigns weight to the features. This is a suitable approach for the purpose or road anomaly detection, based on the fact that the dynamics of the anomaly are similar for the majority of vehicle, but the amplitudes and the frequency of vibrations vary. A hyperplane separating two classes with two attribute values a_1 and a_2 and three weights to be learned w_1 , can be written in the form [97]

$$x = w_0 + w_1 a_1 + w_2 a_2 \quad (5.4)$$

Finding the hyperplane with the maximum margin, can be expressed in the form of support vectors. y is the class value of a training instance l =good, -1 =bad. The maximum margin hyperplane is expressed as:

$$x = b + \sum_i \alpha_i y_i a(i) \cdot a \quad (5.5)$$

, Where, y_i is the class value of training instance $a(i)$, while b and α are the parameters to be determined by the SVM, and a represents a test instance, i.e. $a(i) \cdot a$ represents the dot product of the test instance with one of the support vectors [97]. Two issues can affect the machine learning algorithms, i.e., (i) over-fitting and (ii) computational complexity. Over-fitting is unlikely to occur for SVM. This is because over-fitting is caused by too much flexibility in the decision boundary. The support vectors are global representatives of the whole training points. Computational complexity can be reduced by applying a kernel function before the nonlinear mapping is performed on the feature set.

5

Data labeling

When studying infrastructure anomalies utilizing sensor data, it is important to couple the observed anomalies with a notation about the type and nature of anomalies faced. This process is called "*Data Labeling*". This is particularly important during data collection campaigns in order to reduce the uncertainties associated with the data collection and interpretation, to create a classified knowledge base, and to study the relationship between anomalies, sensor data, and user behavior.

Data labeling is an important step when training the SVM, as it requires that the training set well represents the anomalous signal. Because the anomalies are not always encountered, pinpointing them is a rather difficult process. To label the data during the data collection process, audio-visual capabilities of smartphone may be used to record video footage, take snapshots of the infrastructure, or verbally annotate the anomalies or events. We employ a combined audio-visual method to label anomalies and meticulously annotating every event encountered on the way. We create a detailed list of all known road surface anomalies. As the vehicle approached the anomaly the annotator mentions loudly the type of anomaly encountered. The annotator mentions everything relevant seen or felt while sitting beside the driver or accompanying the wheelchair user. All trips are captured in a video footage with a 480x720 pixel resolution. The video footage will be used later to set the ground truth.

We use a transcription application for movie subtitles to transcript all voice labels with accuracy of about a few milliseconds. The subtitle file is synchronised with the smartphone data timestamp, $t_{acc}^n \leq t_{lab} < t_{acc}^{n+1}$, where t_{acc} is the accelerometer timestamp and t_{lab} is the subtitle time, resulting in an array of $[t_{lab_start}, t_{lab_stop}, label]$.

A lag between labeled segments of the data and the actual encountered anomalies may be noticed as shown in Figure 5.10, where the red signal is

Figure 5.10: Signal in blue and binary label (1 for anomaly and 0 for normal road) in red, generated from the voice recordings.

shifted or does not correspond to any of the peaks. This happens because Android is not a real-time operating system. Consequently, data sometimes may be lost when the device is busy [98] and some measurements may have been delayed, resulting in incorrect timestamps. All lags can, however, be corrected manually.

Training SVM

Finding the best parameters during training phase without leading to overfitting is crucial. This is especially true for road anomaly detection, in which reporting false positive anomalies will cost time and money to the maintenance teams. Assuming that the number of measurement frames containing anomalous encounters is lower than the number of measurement frames containing normal measurements, a 2 step classification procedure will be used.

1. During the first step, all measurement frames are processed to identify measurement frames containing anomalous encounters.
2. In the second step, the measurement frames containing anomalous encounters are further processed to classify their anomalies based on their type.

The training data are not stratified. Stratification is obtained by performing a 10-fold cross-validation, where 1/10 of both anomalies and normal data were used only for testing purpose. Measurement frames with anomalous encounters are those windows that anomalous signal occur in the center of the window spreading equally in both sides. Our rationale here is that using a sliding window method, parts of the same anomaly are present in different consecutive overlapping windows and the aim is to train the detector with the best representative of the class. SVM algorithm uses a radial basis function (RBF) kernel, as described by Burges [99] and Ben-Hur et al. [100]. A RBF kernel K on samples $(a(i), a)$ is expressed in the form of:

$$K(a_i, a) = \exp(-\gamma \|a_i - a\|^2) \quad (5.6)$$

Figure 5.11: Typical example of Self-Organizing Map

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Using a RBF kernel, the feature set is transformed into a higher dimension feature space, where the features are easily classifiable. We perform a grid search to find the best values for the *hyperparameters* [100].

Unsupervised Learning

Unsupervised learning method consists of the process to create clusters of data with similar attributes. For the purpose of clustering different anomalies according to their similarity in pattern and feature set, we use the Self-Organizing Map (SOM) Neural Network [95] [101] algorithm.

SOM is inspired by the way the brain stores and organizes the information, as it stores the correlated information in areas close to each other. SOM creates a bi-dimensional map of neurons in which the input features are grouped through a neighborhood function that calculates the degree of similarity between them. Features representing similar information will be closer on the neuron map.

Figure 5.11 shows typical visualisation of a SOM neuron network lattice. The features are recursively shown to each of the neurons. The neighborhood is characterized by the distance between neurons. Dark colors represent longer distances, the distance is the difference between the pattern features.

We can summarize the behavior of a SOM network in the following steps: Consider a feature set denoted by D , the feature n belonging to D^i , where i is the index of the feature vector. SOM calculates the Euclidean distance of $D^i(n)$ and the weight W of the neurons v . The neuron that produces the shortest distance, also known as the Best Matching Unit (BMU), is indexed u . The BMU has neighboring neurons. The neighborhood radius is restrained with the neighborhood function $\Theta(u, v, s)$. Both BMU and neighbors are updated giving them a weight closer to $D^i(n)$ based on the following formula:

$$W_v(s+1) = W_v(s) + \Theta(u, v, s) \alpha(s) (D^i(n) - W_v(s)) \quad (5.7)$$

, where s is the current epoque no more than a limit λ .

By doing so, a high dimensional space can be mapped onto the plane. One of important SOM's properties is its *topology preserving* feature. This means that feature vectors preserve their relative distance also in the plane. On the other words, the feature vectors that are close to each other in the input space are mapped to nearby neurons in the SOM. This property allows SOM to serve as a powerful clustering tool for high-dimensional data. The SOM network has also a generalization capability, recognizing features never seen before, by assimilating the feature within the neuron it is mapped to.

Based on the aforementioned properties, the extracted features from sensor axis will create a high dimensional feature space with enough information to contribute on clustering together similar patterns. The SOM is trained with the collected data and the formed cluster are manually compared with the known road segments transforming the clusters into labeled classes.

5.2. Driver behavior analysis

5

The more familiar the driver is with the road, the lower is the chance that he/she hits road anomalies. To this end, swerving around known road anomalies occurs often in practice. The swerve can be described as a driver reaction toward the presence of an anomaly on the road surface. Thus, forcing the driver to behave accordingly by steering the vehicle around the anomaly. Our driver behavior analysis service allows detection of various driving manoeuvres and relating them to the road anomalies and driving styles.

5.2.1. Detecting curves

The first step to infer road anomalies by analyzing the driver behavior and manoeuvres is to detect the curves driven by the car. Road engineers divide the road curves into 4 categories, i.e., simple, compound, reverse and spiral, as shown in Figure 5.13.

Figure 5.12: Parameters of the curve

From Figure 5.12, the important features and parameters of a curve and what forces the car staying on the road when following that curve are illustrated.

From analytical mechanics, it is known that: $\omega = \frac{\Delta\theta}{\Delta t} = \theta'$, $v = \frac{a}{\omega}$, $R = \frac{a}{\omega^2}$, $C = \theta R$, where a is the centripetal acceleration, v is the velocity vector, R is the radius of the curve, θ is the angle of the curve, C is the curvature of the curve, and ω is the angular velocity at t_1 .

Figure 5.13: Types of the road curves

Figure 5.14: Swerve transition model

Smartphone gyroscope and accelerometer can provide two of the above mentioned parameters. The gyroscope yaw axis, the one parallel to the gravity vector, measures all the angular changes due to the direction changes of the car, and the lateral accelerometer axis measures the centripetal acceleration. Theoretically, the angle of the curve can be calculated by integrating the angular velocity as expressed in Equation 5.8. However gyroscopes, like all other smartphone sensors, are prone to errors. To calculate the angle of the curve from the gyroscope measurements, the rate of rotation is integrated over time as expressed in Equation 5.8.

$$\theta(t) = \int_0^t \frac{\omega}{\Delta t} \approx \sum_0^t \omega T_s \quad (5.8)$$

Unless Δt is small enough to capture all angular changes, the error of the measurements will also be integrated resulting in the gyroscope drift. A simple method to compensate for the drift is to filter out the error from the signal. For certain cases, a simple filter such as the moving average filter, can be good enough to reduce the drift from the gyroscope. Ideally when the car drives on a straight road, the signal of the gyroscope will be zero. Whenever the sign of the signal changes from zero, it can be inferred that the car is going through a curve. When a car drives through a curve like the situation shown in Figure 5.13.a, the signal of the gyroscope will have a sign corresponding to the direction of the curve. If the direction of the curve is the same as the yaw, the sign of the signal will be positive, otherwise it will be negative. However, if the car is driving over a curve like the situation shown in Figure 5.13.c, the sign of the signal will change following the shape of the curve. The transition point will correspond to the precise moment the signal will cross the axis (as shown in Figure 5.14).

Knowing the angle of the curve, the slope and the sign of the signal, all curves and their directions on the road can be detected. The road curves sensed by the gyroscope can be categorized into:

- Turns, generated by physical turns;
- Swerves generated by the driver or road conditions.

The distinctive feature of these two classes of curves is angle of the curve. Swerves on a straight road segment cannot reach the angle of a road turn. To calculate a rough maximum for the angle of a swerve, let us assume that the average maximum steering angle of a vehicle is $\approx 35^\circ$, the average car width is 1.7 meter, the maximum lane width is 4.7 meter and the car drives with speed of 20km/h (5.5 m/s). The car is performing a lane change from the center of the right lane to the center of the left one in 3 seconds. The calculated angle of directional change to perform this lane change manoeuvre is 17.47° . Thus, we can conclude that when driving with speeds no less than 5km/h (1.39m/s) on a two lane carriageway, the vehicle can safely perform the lane change or the swerve at angles no more than 20° . Hence, the angle of the swerve is inversely proportional to the speed of the car.

All driver manoeuvres can be decomposed into distinctive states. Automotive industry use the detailed chain of manoeuvre states to model drivers behavior. We can distinguish between the type of curves by using the manoeuvre decomposition as a feature. For instance, they decompose the swerves illustrated in Figure 5.14 into detailed chain of states. Examples of "Simple" and "Detailed" states of driving behaviors may look like:

Detailed States

- beginning left lane change
- crossing left dashed lines
- end left lane change
- passing
- beginning right lane change
- crossing right dashed lines
- end left lane change

Simple states

- detected left slope
- peak of left turn
- slope crossed zero
- peak of right turn
- slope crossed zero
- peak of left turn

Curves differ in terms of their angles, radius, and complexity. Figure 5.15 shows the yaw signal for different type of road curves.

Figure 5.15: Labeled x-axis gyroscope signal for a curve and a swerve. Top-left: signal representing a reverse turn; Top-middle: signal representing a swerve at low speed to avoid a pothole; Top-right: signal representing a parallel parking manoeuvre; Bottom-left: signal representing parking in a free parking lot; Bottom-middle: signal representing the third exit at the roundabout; Bottom-right: signal representing U-Turn driving down a hill.

Obviously all these signals have distinctive features. A turn have one direction and a wide angle, a lane change is composed of two or three curves in opposite directions, out of which the third curve usually has a narrower angle. A swerve is composed of three or more curves all having a zig-zag pattern. The parallel parking has the same pattern as the swerve. A parking lot manoeuvre is composed of curves with wide angles, similar to those of turns.

5.2.2. Angle Calculations

Integration of the angular velocity requires a filtered signal to yield an acceptable result. For this particular situation the system uses the wavelet decomposition and the pre-calculated mean feature of the raw gyroscope signal. The mean feature represents the mean for each window of the framed signal. The

wavelet de-noising method and the moving average filter from the mean feature can be applied to filter the signal. The wavelet de-noising and reconstruction will add to computational complexity. The mean of the two consecutive windows is interpolated for the size of the non overlapping windows $W_{size} - \text{Overlap}$, resulting in a moving average filter. We compare the angles calculated by booth methods and have noticed that the results obtained by the mean feature are on par with the wavelet denoising method. Although, for some sharp turns the discrepancy may be in order of 5° , the average angle difference calculated by the two methods is around $= 0.024^\circ$. By defining a minimum threshold Ts_{min} , the integration error and the complexity of the algorithm can be further reduced. The angular velocity is integrated only when the algorithm detects the slope in the mean value of x axis of the gyroscope measurements. The integration continues up to the peak of the curve, if the calculated angle is less than $\frac{1}{2}Ts_{min}$, the calculation drops, the curve is apparently too small. The process of angle integration will restart when another slope is detected or if the signal on its way will cross the zero. This decision is derived by the geometry of the swerve, similar to a sinusoidal wave. The reason for doing so is that some driver tend to calibrate the vehicle by steering in opposite direction before they enter the curve or after they exit it. This will result in a turn preceded or followed by a slight curve in the opposite direction of the turn.

5.2.3. Curve detection

Our curve detection algorithm uses the raw signal from the yaw axis of the gyroscope and the mean feature from the 4th level of approximation of SWT. All the detected curves with an angle more than a Ts_{min} will be considered. The detector uses the following four parameters to detect and classify the curves:

- The first parameter, T_{turn} , filters out all curves that belong to the turn class.
- The second parameter, Ts_{min} , filters out all directional changes whose angles is less Ts_{min} . All vertical and horizontal unevenness of the road will have an impact in gyroscope readings. When narrow angles less than Ts_{min} are detected, they are filtered out.
- The third parameter, T_{bank} , is a complex filter for some cases of banked turns. When the car is driving on a road with banked turn characteristics, a slight continuous curve will be detected. If the banked turn continues for a long distance, it will be detected as a chain of small curves on the same direction whose angles is less than the T_{turn} . T_{bank} checks this curve segments, and if one of them is more than $T_{bank}T$, it is considered to be a turn. When a swerve happens on a banked turn, the signal may not change its sign. These swerves are detected by $T_{bank}S$ that checks the cases when slope fluctuation occurs on a banked curve.
- The fourth parameter, T_{win} , distinguishes between small curves that have

an average angular velocity calculated as the ratio between the angle of the curve θ and the duration of the curve t_θ ,
 $T_{win} < \frac{\theta}{t_\theta}$, less than T_{win} .

Our swerve detection algorithm is described in Algorithm 5.1.

5.2.4. Clustering

One may note that detection of a swerving event is not a confirmation of existence of a road anomaly. To be able to confirm that the swerve was a reaction to a road anomaly, the swerve is required to happen at the same location, within a margin of distance, and confirmed by at least one detected road anomaly. In other words, it should happen n times on a given position. Basically the swerving events and the detected anomalies should cluster together to corroborate the road anomaly.

Our clustering algorithm is described in Algorithm 5.2. The road anomalies and the swerves are clustered together on the basis of their geo-location. First a grid of distances will be calculated between location of all swerves and road anomalies. The location of the reported swerves are more elevated than locations reported for road anomalies because the swerves are performed around the anomaly not precisely at the anomaly spot. To cluster the swerves with the road anomaly and also at the same time to reduce the bias introduced by the GPS inaccuracy, our clustering algorithm double checks the candidate points for the cluster with 2 distance parameters. The first distance parameter is used to establish a cluster of minimal elements that fulfill the distance criteria. The second distance parameter is used to include in the cluster the neighbors of the cluster elements that did not fulfill the first criteria. The rationale behind the second parameter is that swerves are not pinpointed on a map and not in a radial form but rather in a linear form. Compared to a traditional clustering technique like DBSCAN [102], our cluster algorithm excludes the points that do not fulfill the criteria set by the second parameter. Once the cluster is established, the centroid of the cluster is calculated. For short distances of 100m, the distances are calculated considering the earth spherical with the radius of 6371km. The clusters are collaboratively created from reported detection of different vehicles.

5.3. Performance evaluation

In this section, we present our methodology for performance evaluation of our techniques to enable services for road infrastructure monitoring and the results obtained.

5.3.1. Experimental setup

To perform experiments, we use 2 Android smartphones, 1 Galaxy S2 smartphone, and 1 Galaxy S4 Mini smartphone. The sampling rate for the Android smartphones were set at 96Hz, while for the Galaxy S2 and S4 Mini smartphones were set at 63Hz. The smartphones were fixed horizontally on the

Algorithm 5.1: Swerve Detector Algorithm

Input: Signal of the Gyroscope S
Output: Integrated signal $\bar{S}$
 $I_S \leftarrow \text{Interpolate}(S);$
 $\Phi \leftarrow \text{Slop}(S);$
 $i \leftarrow 0;$
 $j \leftarrow 0;$
 $k \leftarrow 0;$
 $T \leftarrow \emptyset;$
 $SE \leftarrow \emptyset;$
while $S \neq \emptyset$ **do**
 if $A_i \geq 2$ **then**
 $\bar{S}_j \leftarrow \bar{S}_j + A_i;$
 else if $A_i == 0$ **then**
 if $\bar{S}_j > T_{turn}$ **then**
 $TU = TU \cup Turn;$
 $k = 0;$
 else
 if $(k == 2) \&\&((SLOP(j-2) * SLOP(j-1) > 0) \&\&(SLOP(j-1) * SLOP(j) > 0))$ **then**
 if $A_{\bar{S}_{j-1}} \in [T_{turn}, T_{smin}]$ **then**
 if $abs(A_{\bar{S}_{j-2}} + A_{\bar{S}_{j-1}} + A_{\bar{S}_{j-1}}) < SET$ **then**
 $SE = SE \cup e;$
 else
 $k \leftarrow k + 1;$
 $(A_{\bar{S}_{j-1}} + A_{\bar{S}_j}) \ j \leftarrow j + 1;$
 $i \leftarrow 0;$
 $i \leftarrow i + 1;$
 $S \leftarrow S \setminus I_S;$

Algorithm 5.2: Cluster algorithm

Input: All points with geo-location P
Output: The sets of clusters Θ
 $RemainingPoints \leftarrow P$;
 $\Theta \leftarrow \emptyset$;
 $Q \leftarrow \emptyset \cup 0$;
while $RemainingPoints \neq \emptyset$ **do**
 if $Q \neq \emptyset$ **then**
 $R \leftarrow Q$;
 $Q \leftarrow \emptyset$;
 for $r \in R$ **do**
 if $D(r, r.N_j) < d$ **then**
 $\Theta_i = \Theta_i \cup r$;
 $Q = Q \cup r.N_j$;
 $RemainingPoints \leftarrow RemainingPoints \setminus r$;
 else
 $i \leftarrow i + 1$;

¹Clustering algorithm variables

P : the set of all points; Θ : the set of clusters; Q : set of points to be expand with breadth first behave; R : running set of points; $D()$: the function check distances between points; r and all of its neighbor points; $r.N_j$ is the neighbor point of point r ; d : predefined cluster diameter;

windshield inside car, with the back camera facing the road ahead. The data were collected from different type of roads in and around the city of Vlora in Albania as well as in the city of Enschede in the Netherlands. These roads represent completely different environments. Crowded, busy, and sloppy roads in Albania versus flat roads with regulated traffic in the Netherlands. Table 5.1 shows traveled distances, road types, and vehicles used to collect the data. The labeled data were from trip 2, 3, and 6. All cars were driven by different drivers. Trip 4 lacks a video footage, while trip 5 has a video footage but lacks GPS fixes. Trip 7 represents an aggressive driving behavior.

Table 5.1: Total road coverage in km with different vehicles

Trip	Car	Type	Km	Area	Hz	Location
1	Toyota Corolla	HB	22.8	rur/urb	54	E(NL)
2	Peugeot 306	HB	22.8	rur/urb	107	E(NL)
3	Skoda Fabia	SM	16.3	urban	54	V(AL)
4	Toyota Yaris	SM	33	hwy/rur	54	V(AL)
5	BMW X3	SUV	5.46	urban	54	V(AL)
6	Citroen C3	SM	33	urban	130	E(NL)
7	VW Golf	HB	5	urban	130	E(NL)
Total / Unique			138.7 / 80.6			

HB= HatchBack, SM= SuperMini, rur=Rural Road, urb=Urban Road, hwy=High Way, E=Enschede, V=Vlora

5.3.2. Performance evaluation of road pavement anomaly detection

The results from the training the anomaly detection classifier, presented in Table 5.2, clearly show that the algorithm trained with the demodulated features is more accurate than the algorithm trained with raw data.

Table 5.2: The confusion matrix and accuracy for the classification of anomalous (Positive) and normal (Negative) segments of road, with different feature sets.

Method	Confusion Matrix Anomaly vs Normal											
	Accuracy	TP	TN	FP	FN	Spec.	Sens.	Prec.	G	RS	FPR	FNR
TD _{raw}	81.43%	49	201	39	18	0.82	0.73	0.196	0.77	0.89	0.18	0.26
TD _{demodulated}	85.26%	52	214	31	15	0.87	0.82	0.1955	0.84	0.94	0.13	0.18
FFT _{raw}	77.88%	49	194	51	18	0.79	0.73	0.2016	0.76	0.92	0.21	0.27
FFT _{demodulated}	79.17%	40	207	38	27	0.84	0.59	0.1619	0.71	0.70	0.15	0.40
SWT _{raw}	82.69%	50	208	37	17	0.85	0.75	0.1938	0.80	0.88	0.15	0.25
SWT _{demodulated}	88.14%	57	218	27	10	0.89	0.85	0.2073	0.87	0.96	0.11	0.15
TD+FFT _{demodulated}	83.01%	48	211	34	19	0.86	0.72	0.1853	0.79	0.83	0.14	0.28
TD+SWT _{Demodulated}	88.78%	59	218	27	8	0.89	0.88	0.213	0.89	0.99	0.11	0.12

*TD= Time Domain, *FD= Frequency Domain, *SWT=Stationary Wavelet Transform

TP/FP= True/False positive, TN/FN= True/False negative, Spec./Sens.=Specificity/Sensitivity, Prec.=Precision

G= G-mean, RS= Rlative sensitivity FPR/FNR = False positive/negative rate

Table 5.3 shows anomaly classification results of our 10-fold cross-validation

training of the data with features extracted from the wavelet decomposition (SWT) and combined (TD+SWT) features from time domain and wavelet decomposition. The accuracy is the same 91%. However, the severe class is more accurately detected with features from the wavelet transformation only.

Table 5.3: The confusion matrix and accuracy of the classification for anomalous segments of road with features from SWT and TD+SWT.

Confusion Matrix							
Class	SWT			TD+SWT			
	Sev.	Mild	Span	Sev.	Mild	Span	
Severe	17	3	0	16	4	0	
Mild	1	15	0	0	16	0	
Span	0	0	9	0	0	9	
Accuracy	91.1%			91.1%			

5

Evaluation on unlabeled data

The evaluation process turned out to be easy using our labeling technique. The system made the predictions and two subtitle files were generated containing the labels of the anomalies detected. The algorithm also generates a KML ² file with the location of severe anomalies for Google Maps. We went through the video footage taking notes on reported anomalies from the subtitles. From data collected in Albania some types of severe anomalies were not detected. We believe the reason for that is the fact that our system had not been trained for those anomalies. Table 5.4 shows performance of our system with data collected with different vehicles in different locations. Trip 1 and Trip 2 are made in the Netherlands, on the same road used for training the system. Trip 3, 4, and 5 are trips made in Albania (see Table 5.1). Trips in the Netherlands have a higher ratio of anomalies per total number of windows than those in Albania. This is related to the driver behaviors in our tests. The video footage showed that the drivers in Albania tried to avoid road anomalies and in particular road damages by swerving around or slowing down in front of bad road areas, whereas the drivers in the Netherlands did not do so. The GPS location from smartphones on the map was not always very accurate (see Figure 5.16). Having more data from different drivers, it is possible to better cluster all measurements on the basis of their geo-locations.

To evaluate performance of the anomaly detection algorithm for severe class, we counted the false negative windows reported by the algorithm and also the undetected anomalies from the video footage (See Table 5.4). The algorithm detects all windows with anomalous signal, including consecutive windows for the same anomaly. To avoid cluttering on the map if two or more consecutive windows detected the same anomaly, we keep half of them. By doing so, the number of anomalies shown on the map is fewer than the number of

²Keyhole Markup Language <https://developers.google.com/kml/documentation/kmlreference>

Table 5.4: The results of system classifications with models and features from TimeDomain and Wavelet Decomposition

			Detection	Classification			Mapping	Evaluation			
S/R #Win			Anom	Sev.	Mild	Span	mapped	Sev.	TD	FD	MA
Trip 1	TD 47Hz	609	195	107	68	20					
	SWT 47Hz	609	165	119	26	20	113	73	64	15	4
Trip 2	TD 96Hz	764	222	76	105	41					
	SWT 96Hz	764	207	93	72	42	123	61	52	12	3
Trip 3	TD 47Hz	1067	280	119	106	55					
	SWT 47Hz	1067	222	120	51	512	152	82	74	10	8
Trip 4	TD 47Hz	2240	584	349	176	61					
	SWT 47Hz	2240	412	255	98	59	296	173	no video		
Trip 5	TD 47Hz	794	239	113	126	0					
	SWT 47Hz	794	192	99	93	0	134	76	74	6	6

Sev.= Severe, TD= True Detections, FD= False Detections, MA= Missed Anomalies

mapped= Nr. of anomaly points pinpointed on the map

Figure 5.16: Snapshots of map and video anomalies for locations in Vlorë, Albania.

reported windows. As false detections (FD) were counted all severe anomalies that were detected as mild ones, but that can be subjective based only on video footage. Missed anomalies (MA) is the number of all anomalies, counted by us through the video but not reported from the detector. For Trip 4 associated with Figure 5.5, the video file was corrupted, but based on GPS map we noticed that the majority of the anomalies were in the segments of deteriorated road, the segment between black lines. For Trip 5, made with the BMW X3 SUV, the results were more correct. Worth mentioning is the fact that the system has a high accuracy on detecting transversal anomalies, spanning the width of the road. On extremely deteriorated road segments, the system detected windows that belong to the transversal anomaly class, see Table 5.4. In comparison, P^2 [34] and Nericell [35] skipped the windows representing transversal anomalies.

5.3.3. Performance evaluation of driver behavior service

Training the classifier will aim to find the best filter parameters that best represent the entire dataset. We conduct an exhaustive parameter grid search through all our labeled data. The confusion matrix, accuracy, specificity, sensitivity, recall and f-score were calculated for every iteration. The results were compared and the best parameters were selected by analyzing the f-score, precision, and recall for the swerve and the turn classes. Figure 5.17 shows the calculated f-score through a deep iteration method with increasing threshold values. Once the best parameters were found, we conducted a test on unlabeled data. The detected swerves, curves, and road anomalies were checked with the map and the video footage. Consequently, the false positives (FP) were discarded and the false negatives (FN) were used to label the data. This way the unlabeled data becomes partially labeled, another training and testing session is conducted.

Figure 5.17: F-score of the detector for $Tt_{filt} = \{0^\circ, \dots, 20^\circ\}$ for $Ts_{min} = \{0^\circ, \dots, 4^\circ\}$, T_{bank} and T_{win}

Effect of parameters

The most important parameters used in our driver behavior analysis service are the Tt_{filt} and Ts_{min} . The T_{bank} and T_{win} are mostly auxiliary filters that help reducing the number of false negatives for the swerve and the turn class. It is therefore important to analyse effect of these parameters and filters on accuracy of our algorithm. To do so, we calculate the Positive Predictive Value (PPV) and the True Positive Rate (TPR) using the following equations:

$$PPV = \frac{\sum TP}{\sum TP + \sum FP} \quad (5.9)$$

$$TPR = \frac{\sum TP}{\sum TP + \sum FN} \quad (5.10)$$

Table 5.5 shows the confusion matrix before and after filter $T_{bank}S$ is applied. Overall, applying $T_{bank}T$ led to increase of the PPV by 4.1% for the turn class, while applying the $T_{bank}S$ led to increase of the TPR by 12.7% for the swerves class.

Table 5.5: Confusion matrix before and after tuning the filter parameters

ConfMat before the T_{bank} & T_{win} applied							
	Straight	Swerve	Turn	TPR	SPC	PPV	F-score
Straight	223	14	9	0.91	0.86	0.92	0.91
Swerve	16	30	1	0.64	0.95	0.64	0.64
Turn	3	3	85	0.93	0.97	0.89	0.91
ConfMat after the T_{bank} & T_{win} applied							
Straight	226	15	5	0.92	0.90	0.94	0.93
Swerve	10	36	1	0.77	0.95	0.68	0.72
Turn	4	2	85	0.93	0.98	0.93	0.93

Evaluation of clustering algorithm

To evaluate the performance of the clustering algorithm, repetitive laps were driven at the campus of University of Twente. We swerved around manholes on the roads. Each time the driver behaved differently by swerving around that point with different speeds and angles. Also some random swerves were performed at random locations. The clustering algorithm clustered all emulated anomalies within a certain radius. To find the best cluster parameters that define the radius of the cluster, we took into consideration the error of the GPS, the maximum turning angle, and the distance between the peak of the swerve and the point of anomaly. To tune the radius parameters, the same aforementioned technique of exhaustive search was performed. Figure 5.18 shows results of our performance evaluation. Represented by red circles are the parking spaces on the campus. The bike icons represent clusters formed in cross-intersections of bike paths with road. This type of intersections, where the road deviates from a straight line are common to the Netherlands.

Detecting parking manoeuvres

The parking manoeuvres consist of a set of turns preceded or followed by a stationary state. We make use of this simple fact to detect the parking event in order to distinguish these manoeuvres from swerves. By decomposing the states of the parking manoeuvre, it is possible to distinguish between a parallel and parking lot parking. Figure 5.15 shows how different these two parking types are. Parallel parking is composed by small angle turns in opposite directions, similar to the swerves or lane changes. Figure 5.15 Parking lot shows that the manoeuvre consists of two big curves on the same direction. The first one is a reverse turn on the left, followed by a right turn. The direction of the velocity vector, calculated from the centripetal acceleration and angular velocity $\mathbf{v} = \frac{\mathbf{a}}{\omega}$, shows the direction of the manoeuvre, if the turn performed is in reverse or not. The stopping state of the vehicle, is detected by analyzing the variance feature of gyroscope and accelerometer.

Evaluation on unlabeled data

Figure 5.19 shows the results of the algorithm on unlabeled data. The results were manually checked on the map and confirmed through the video footage.

Figure 5.18: Clustering the turns, all the clusters are precise on showing the tip of the turn. In circles are shown the manoeuvring turns for the parking lots.

Overall the algorithm performed very well on the swerve class, with a True Positive Rate $\approx 87\%$. The turn class scored a TPR $\approx 97\%$. PPV for the swerve class is 70% and for the turn class is 95%. The FP detections on the turn class are indeed FN of the swerve class, ie swerves classified as turns. On the Netherlands roads, the algorithm performed very well in detecting the curves, but not so well in discriminating straight segments from swerves. The Dutch roads have in common some road and bike path intersections. These intersections expand the sides of the road, resulting in a smooth turn. We labeled these places as turns, but occasionally when they are short or approached fast they behave like swerves.

False Discovery Rate (FDR) of our algorithm on unlabeled data is 30% for the swerve class and 5% for the turn class. However, the FDR of 30% of the swerve class is not considered a major concern for the overall performance of the classifier. The position of the FP swerves should cluster to be considered as real swerves.

Figure 5.19: The serves and turns detected for every trip, True Positive and the False Positive are reported, the last three trips are made in Albania

The chaotic traffic in Albania resulted in detecting a great number of swerve events. Nevertheless, our algorithm was able to detect all serves related to the road anomalies. The FP detections were related to the swerves caused by the driver steering wheel calibration or the pavement unevenness. The majority of the swerving were manoeuvres to overtake parking cars in the lane or other obstacles. The last trip (Trip 11) driven through a highway and a rural road lacks the video footage. The FP reported were those we counted on the map. For the swerve class we counted as the FN the swerves reported on a turn. For the turn class, the FP were curves reported on a straight path. The reported swerves on the highway were only the FP ones. The TP for the turn class are 77%. The reason is that on highway the angle of turns is small, whereas the radius is wide and these turns are banked ones. FP of the swerve class happening in

the rural deteriorated roads, are miss detected as turns for the only reason that the road was very deteriorated and the manoeuvres involved turning around those anomalies.

From the overall number of the swerve classes, some lane changes were detected as two swerve events. This happened when an overtaking manoeuvre was performed as follow: lane change left/ long straight/ lane change right.

Accidental vs. Periodic swerves

All the discovered turns and swerves were clustered together. The results obtained from the cluster are shown in Table 5.6. These results represent the number of cluster obtained from all the trips of Figure 5.19. Overall 15 swerve clusters were due to road pavement anomalies. All parking events were clustered together. Once identified, these parking spots can be blacklisted. The overtaking manoeuvres were also clustered together for high speed segments of roads, but on those segments no anomaly was detected making these clusters irrelevant.

Table 5.6: Clustering resultes, all swerve, turn detected and true positive anomalies

	Cluster	Points	Anomaly
Swerves	49	120	15
Turns	75	277	
Total	124	397	15

5.4. Summary

This Chapter described the RoADS algorithm that detects road surface anomalies using mobile phones equipped with inertial sensors: accelerometers and gyroscopes and drivier behavior analysis. Stationary wavelet transform analysis and a method to remove effects of speed, slopes and drifts from sensor signals using the envelope technique is also described. Our audiovisual labeling technique was precise and also helpful for the system evaluation. Classifying road anomalies is a rather difficult process and the expectancy to detect all road anomalies on one pass are quite low. Nevertheless, the obtained results showed a consistent accuracy of $\approx 90\%$ on detecting severe anomalies regardless of vehicle type and road location. To address the problem when the driver steers away and intentionally skips the anomaly, a behavior detection algorithm is implemented. Meticulously studying the features of road curves and a conditional classification technique, we were able to build a reliable swerve detection system to complement the RoADS system. Overall the TPR of the detector for the swerve class is 70%. During our experimental phase we confirmed 15 road anomalies, by clustering the detected swerves with previously detected anomalies by RoADS. Apart from the swerves, the detector can also detect the angle of the turns in the road with an overall average error of 5° and an average error of 2° for the turns with an angle less than 15° . Another

positive feature of the detector is the ability to detect and distinguish between parking lots and sidewalk parking. The detector performed well on urban environment where the speed is limited. On deteriorated or unpaved roads the performance falls but it does not affect the overall detection rate, because the RoADS performed very well on deteriorated roads.

6

Transport infrastructure monitoring indicators

Providing a real-time overview of health and condition of the ground infrastructures can substantially reduce the costs of maintenance as well as accident rates.

Only certain profile wavelengths are considered harmful for the road pavement or track railway and these wavelengths fall into the diapason of the modern smartphone sensing capabilities. It is obvious that smartphones are not as accurate as the high-end measurement vehicles. However, multiple measurements made by different drivers/ cyclists and train passengers on the same infrastructure segments over and over during day/ week/ month/ year is a powerful asset, which can compensate for inaccuracy and uncertainty of smartphone data providing that high temporal and spatial resolution data is collected and processed by optimized machine learning techniques. This is the main concept behind our smartphone-based framework called RoVi to enable crowd sensing-based monitoring of transport infrastructures.

RoVi enables engineers and authorities to:

- prioritize the measurement campaign schedules, by reducing the frequency of inspections, which translates into substantial financial benefit.*
- trace the development of road/ track defects,*
- forecast the defects and deterioration.*

This chapter is based on:

RoVi: Continuous Transport Infrastructure Monitoring Framework For Preventive Maintenance. In: *Proceedings of the IEEE International Conference , PerCom 2017*, pp. 1-6. IEEE Computer Society.

Before proceeding further into details of RoVi and since we aim to design a general technique to be used for all transport infrastructure types, we have to develop a mechanism that automatically detects the transport mode. In what follows, we first explain this mechanism.

6.1. Automatic transport mode identification

For the context manager (described in Chapter 3) to work properly and to seamlessly switch the services based on the infrastructure being monitored, we design a classification algorithm to distinguish between the transport mode classes including traveling by bikes, cars, and trains. Our classification algo-

Table 6.1: Dataset pool

	Nr.instances	Speed bins 2ms wide	Training instances
Bikes	517591	6	30000
Automobiles	564318	16	30000
Train	246990	22	30000
Total	1324592		90000

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rithm is based on a linear SVM machine learning. We train the algorithm with only 3 features, i.e., the RMS, the variance and the average speed of the first level of details SWT as explained in Chapter 4. First level of details correspond to the highest part of the half band pass filter. From all available collected datasets with different vehicles, a pool of features is created. Using our data collection tool, explained in Chapter 4, we collect data from various types of transport infrastructures using smartphones. Overall our collected dataset consists of 1,324,592 feature vectors. Table 6.1 shows an overview of this dataset.

Table 6.2: Confusion matrix: training data and all dataset

Training data			
	bike	automobile	train
bike	29454	218	328
automobile	2470	26826	704
train	331	1090	28579
All data set			
	bike	automobile	train
bike	422216	3257	4442
automobile	40745	437445	11318
train	2320	7575	205252

We select the training instances randomly for each class of transportation mode and train the classifier and cross validate it with a 10-fold cross validation. Table 6.2 shows the confusion matrix of the training dataset as well as

the testing data set. The accuracy of the training data is 95.3%. The model is applied over the entire dataset and the accuracy is verified again.

Next, we analyze the false positives in terms of speed for each class of transportation modes. Figure 6.1 shows overall number of segment data for different speed ranges for each transportation mode. For the automobile class, the majority of false positives are concentrated in the 1 bin (0 - 2 m/s) and consequently they are mostly misclassified as bikes. The reason is that the segments in the first bin happen when the speed of the vehicle is close to zero, most of the time during a traffic congestion. We studied further this phenom-

Figure 6.1: Testing predictions for three classes on three traveling mode datasets

ena to understand how long the algorithm needs to run from the start of trip to correctly classify the transportation mode. The results from Figure 6.2 show the percentage of true positives for a period of time, in windows increasing from 1 to 300, from the start of the trip. It is obvious that once the vehicle reaches the cruise speed the accuracy increases enough to correctly detect the transportation mode. 300 samples corresponding to 100 seconds from the start of the trip are sufficient to classify correctly more than 50% of the windows. During our tests we correctly detected the transportation mode 100% of times

Figure 6.2: Percentage of correct detections for different periods

6.2. RoVi - A smartphone-based framework for transport infrastructure monitoring indicators

RoVi is a versatile framework that runs as a service on Android phones. It uses a built-in signal processing method to decompose and filter motion signals collected by the smartphone to extract the frequencies of interest caused by the profile waves. Extracted signal features are used to calculate the roughness and slope angles of the profile. These results can be used locally or transferred to the cloud to be clustered and provide a granular view of the infrastructure segments and deterioration trends.

Our driver behavior algorithm, presented in Chapter 5, is used to detect the lane changes.

RoVi and its associated sensor data analytic tool performance is evaluated for three different infrastructure types, i.e., roads, bike paths, and railroads. The ground truth for performance evaluation was collected by the state-of-the-art measurement vehicles, i.e., the ARAN for roads and the TGC for railroads. Through this evaluation, we show that RoVi is reliable, accurate, and cost-effective to be used for continuous monitoring of ground infrastructures.

6

6.3. Methodology used in RoVi

The main components of Rovi are: (i) sensor data analytics to extract technical features of the transport infrastructure, (ii) adaptive signal processing by zooming in and out the frequency band, (iii) geo-location visualization, and (iv) lane detection. In what follows we describe our approach for each of these components.

6.3.1. Feature calculation

An important quality indicator for monitoring of road segments is IRI (International Road Index), formally calculated using Equation 6.1, where L is the profile length, Z_s and Z_u are the acceleration of the sprung and unsprung mass, respectively. According to [20], IRI is influenced by wavelengths ranging from 1.2m to 30m, with the highest response for the wavelengths around 2.4m and 15m.

$$IRI = \frac{1}{L} \int_0^L |Z_s - Z_u| dx \quad (6.1)$$

For track geometry monitoring, the angle of slope is derived from Equation 6.2, where h_t is the rail elevation, and $2b_0$ is the width between the center of the rails around 1500 mm. From there, h_t can be derived by calculating the inclination angle φ_t using the smartphone data. While cant is fundamental for the operation of the railroad, twists are vertical irregularities of the tracks and should not be allowed to pass certain thresholds. Because the height of twist is smaller for a given profile length, they are measured at lower frequencies.

$$\varphi_t = asin \frac{h_t}{2b_0} \quad (6.2)$$

6.3.2. Adaptive signal processing

As pointed out in the Introduction, Chapter 1, infrastructure engineers estimate the state of the infrastructure based on profile measurements with parameters expressed in wavelength λ (sinusoid length in meter) and the gradient of the slope. The sinusoid equation Y with amplitude A as a function of x is expressed as:

$$Y = Asin(\frac{2\pi}{\lambda}(x - x_0)) \quad (6.3)$$

A traveling sinusoid is expressed mathematically in terms of velocity v , wavelength λ , and frequency f . From Equation 6.3, the wave velocity determines the distance $x_0 = vt$. Now the sinusoid can be expressed as:

$$Y(x, t) = Asin(\frac{2\pi}{\lambda}(x - vt)) = Asin(2\pi(\frac{x}{\lambda} - ft)) \quad (6.4)$$

The temporal frequency of a traveling sinusoid is expressed as:

$$f = \frac{v}{\lambda} \quad (6.5)$$

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From the above equations, one can conclude that to achieve a high spatial resolution, the measuring vehicle, being ARAN or TGC, should be equipped with sensors having very high sampling rate and high signal to noise ratio.

According to Nyquist sampling theorem [25], if a function $Y(t)$ contains no frequencies higher than B Hz, it is completely determined by giving its ordinates at a series of points spaced $1/(2B)$ seconds apart. In other words, Nyquist sampling rate is the rate at which the signal must be recorded in order to accurately reconstruct the original signal. A given pothole on a given road will present different frequency signatures depending on the speed of the vehicle passing through it, even though it has a fixed spatial signature. For example, a smartphone sensor with a sampling rate of 100Hz can measure sinusoid with frequencies up to 50 Hz. However, that signal is compromised by the high level of noise related to the inaccuracy of the sensor and position of the device. Additionally, smartphones sensors also measure multiple other signals not related to the infrastructure geometry, for example wheel and engine revolutions. These continuously changing frequencies affect the nature of the signal, making it transient and non-stationary. All existing solutions suffer from the problem of speed dependencies of inertial sensor amplitude, and none of them has addressed this problem from the frequency modulation perspective. They do not consider the relationship between temporal and spatial analysis. Based on the Nyquist theorem, if the speed of the vehicle is too high, the frequency representing the pothole will also be too high and as such will not be recorded

Figure 6.3: Spectrogram of a 100 m profile from different measurements. a) raw signal b) signal related to IRI frequencies

by the smartphone. Knowing these limitations and implications, we process the signal in a certain way to extract the features with meaningful information regarding the infrastructure wavelength components. Figure 6.3 shows a 100m profile measured 100 times with different speeds, from Figure 6.3 a) we can see that wavelength affecting IRI are buried under high frequencies. Figure 6.3 b) shows the correlation of all measurements, despite travelling speed.

A signal is considered non-stationary when its frequency or spectral content change with respect to time. Recovering the signal only from the waveforms related to the infrastructure geometry requires the implementation of signal decomposition methods capable of providing a time frequency representation of the signal. The frequency representation is obtained through transformation of the time series signal. The output of this transform is the inner product of a family of basis functions with the signal.

Before getting sensed by the sensor, the signal is affected by outside factors, like the vehicle damping system and the position of smartphone in the vehicle. These factors act like filters with a certain frequency response. For example vehicle dampers filter vibrations that affect driving comfort at 1Hz and 10Hz or the cant deficiency in trains is compensated by tilting of the coach at 60%-70%. This implies that calibration based on the vehicle and the position of the smartphone inside the vehicle is very important and in fact needed. Assuming that the smartphone will not be moved throughout a trip, these filtering effects can be considered stationary and a calibration phase will compensate for their effects. For the calibration phase, an auto-regression (AR) predictive filter, is used, based on the coefficients of the decomposition of the past values as described by Renaud et al. [103], to predict the frequency response and long term effect of these factors. The calibration phase is meant to remove the stationary vibration components generated by the internal components of the vehicle (e.g. the engine). As explained in [56], once the autoregressive (AR) predictive filter is applied to the signal collected by the smartphone, we are left with the non-stationary part of the signal, which is generated by the road roughness only.

The obtained transformed and filtered signal contains most of the profile and geometry impact information.

6.3.3. Lane detection

Most of modern transport infrastructures consist of multi-lanes/tracks and they can deteriorate at different rates although they are essentially part of the same infrastructure and at the same location. For example a multi-lane highway segment deteriorates faster on the right side of the direction than on the left side [104]. This has to do with the traffic rules, as most left lanes are used for overtaking also by the heavy cargo trucks. The same reasoning goes to the railroad tracks near intersections or big multi-track stations. This issue represents a lane detection problem. In automotive industry the activity of changing lanes is decomposed into two steps manoeuvres, i.e., a lateral movement phase followed by a stabilisation phase. The sign of that lateral move-

ment contains the information about the lane being on the left or the right. In [65], we described a method to detect different situations, one of which is the lane change activity, caused by driver behaviors. The algorithm uses the gyroscope Jaw data to detect all direction changes and classifies them into different classes. Whenever a lane change is detected, the measurement profile will be assigned with an incremental $L(n)$ for left lanes or $R(n)$ for right lanes. Trains change tracks utilizing special systems called *switches*, resulting in an increase in vibration and a lateral displacement. However further studies should be conducted to accurately detect track changes.

6.4. Performance evaluation

The evaluation of the RoVi framework was conducted through extensive experiments involving different type of vehicles, bikes, and trains riding on various road and railroad segments. In all these experiments, GPS, accelerometer, and gyroscope data were recorded using smartphones and post-processed of-line using RoVi components explained in Section 6.3.

Figure 6.4: Cross-correlation (in left) and Power Spectrum Density (in right) of the smartphone measurements placed in ARAN and in Mazda

Figure 6.5: Power spectrum density low-pass filtered for ARAN and Mazda

Table 6.3: Experimental setup inventory

SmartPhones								
Nr	Type	Android OS	Sensor					
			acc		gyro		GPS	A
			avg S/R	max lag(ms)	avg S/R	max lag	S/R	
1	MotoG	5.1	99Hz		184Hz		1Hz	M
			10.2	175	5.4	172.2		
2	Samsung S4 mini	4.4.2	76Hz		132Hz		1Hz	S
			13.2	1137.1	7.5	1135.5		
3	OnePlus One	5.1/6	120Hz		198Hz		1Hz	O
			10.2	175.1	5	170.7		
Framework								
Trip Nr	Start	Stop	Length		Vehicle		SPhone	
I Train								
1	Amersfoort	Utrecht	18.6km		UMF120		4xM,4xS	
2	Utrecht	Hogebrug	24.3km		UMF120		4xM,4xS	
3	Utrecht	Leiden	48.8km		UMF120		4xM,4xS	
4	Leiden	Utrecht	48.8km		UMF120		4xM,4xS	
5	Enschede	Zwolle	63.4km		NS DM90		S	
6	Enschede	The Hague	192km		NS VIRM		2xS	
7	Enschede	Schiphol	163km		NS ICM		S	
II Cars								
1	Deurningen	Enschede	8.5km		ARAN		S	
2	Deurningen	Enschede	3x8.5km		Mazda CX5		M,2S	
3	Deurningen	Enschede	40x8.5km		Audi A4 coupe		M,S	
4	Deurningen	Enschede	2x8.5km		Citroen C4		M,O	
5	Hoogland A1	Eemnes A1	3x7.2km		BMW 5		O,S	
6	Eemnes A1	Hoogland A1	3x7.2km		BMW 5		O,S	
III Bikes								
1	Enschede(urban)		152.16km		Bike1		M	
2	Urban,Forest,Highspeed		221.67km		Bike2		S	
3	Urban		253.15km		Bike3		S	
4	UT campus		47.43km		Bike4		S	

6.4.1. Experimental setup - ARAN measurement campaigns

The ground truth data were collected through initial experiments using the state-of-the art measurement vehicles, i.e., ARAN for roads and TGC UFM120 measurement train for railroads. To collect the ground truth, a set of smart-phones were placed inside these vehicles and measured simultaneously with the measurement vehicles the infrastructure profiles. Some smartphones were fixed while some were loosely placed on the dashboard or on a seat. The data collection over the railroad was performed over a 140 km track from Amersfoort to Utrecht, Hogebrug, Utrecht, Leiden, and Utrecht stations. The ground truth data about the road was collected by the ARAN vehicle on N737, i.e., a

regional road from Deurningen to Enschede.

Other measurement campaigns for roads were carried out by four different types of cars (Mazda CX5, BMW 5, Audi A4 Coupe, and Citroen C4) on two highway segment lanes on A1 from Hoogland to Eemnes as well as on the N737 regional road. Railroad measurement campaigns were performed on passenger trains from Enschede to Zwolle, Enschede to Den Haag, and Enschede to Schiphol. 500 km of bike paths were cycled, while four smartphones mounted on four bikes were recording data. Table 6.3 gives the full overview of our experimental setup for different transportation means and segments.

6.4.2. Road roughness index - ARAN measurement campaigns

While ARAN was collecting the ground truth measurements, we followed it by a Mazda CX5 equipped with smartphones to investigate the impact of the suspensions inside the vehicle. Smartphones were placed in both ARAN and Mazda by attaching them to the vehicle's windshield using the same holder model stated in Table 6.3 II(1,2). Various other experiments were carried on the same road segment later by other vehicles as described above as well.

Figure 6.4 shows the cross-correlation between measurements of the smartphones in ARAN and Mazda. From the right graph, it is difficult to distinguish the similarities because the signal is buried in noise. However, in the filtered signal the cross-correlation is clear and has a lag of -4.02 sec, which is basically the time distance between Mazda following ARAN. The Power Spectrum Density graph (in the right) obviously shows that the signal has comparably the same power, but there is a shift in main frequency bins. ARAN smartphone signal peak is at 19Hz, while Mazda smartphone measurement peak is at 17Hz. This difference in PSD is related to the vehicle characteristics. Figure 6.5 shows the PSD of low-pass filtered, 1st level of wavelet decomposition, signal for both ARAN and Mazda. ARAN has more energy at 1Hz, 10Hz to 15Hz, since these frequencies interfere with passenger comfort [20] they are more attenuated on normal vehicles compared to the *golden car* (ARAN).

We calculated the RoVi roughness coefficient ($RoViIRI$) based on the approach explained in Sections 6.3.1 and 6.3.2 for the measurements collected by the smartphones placed inside the ARAN vehicle and the Mazda and compared them with the IRI values received after two weeks from the company running ARAN measurement campaign. Thereupon we learned the hard way, the effect of Android sampling lag on the measurements. Both cars used Samsung Galaxy S4mini smartphones sampling at 76Hz and additionally recording the video footage of the trip. The lag in certain segments was larger than the profile length, resulting in some profiles having no samples. In total, the road segment has a length of 8460m resulting in 846 profiles of 10m. Android sampling lag resulted in absence of information for 72 profiles for ARAN data and 19 profiles for Mazda.

Due to the fact that IRI reports the roughness of the pavement under the tire, it is difficult to get the exact same values for the same segment of road. Since it is quite improbable to travel through the exact same profile, we consider IRI

values as a whole number and round the values to the nearest integer. Comparing each IRI profile with the reported *RoViIRI*, for a quantitative numerical evaluation purpose, is quite difficult. This is due to coordinate calculations of the profile from Smartphone GPS and the fact that GPS accuracy introduces an inconsistency on reported *RoViIRI*.

Considering this, there will be a continuous shift back and forth on the reported IRI on adjacent profiles. ARAN builds the profile lengths based on the shortest one, which is 10m. This makes a 100m profile an average of 10X10m profiles. Results and comparison with IRI are shown in Table 6.4.

Table 6.4: Comparison between results of ARAN IRI and *RoViIRI* for all the tested roads

Road	Number of profiles	IRI index									
			1	2	3	4	5	6	7	8	>9
Enschede	ARAN	10m	8	513	242	57	12	7	5	1	2
		100m	3	51	26	5	0	0	0	0	0
	<i>RoViIRI</i> 40 trips	10m	11	521	220	57	18	13	2	3	0
		100m	0	53	27	3	0	1	0	0	0
Amersfort A1L Left	ARAN	10m	341	250	21	6	6	0	0	1	0
		100m	31	29	3	0	0	0	0	0	0
	<i>RoViIRI</i> 5 trips	10m	68	286	145	68	33	13	6	3	2
		100m	9	40	9	4	1	0	0	0	0
Amersfort A1R Left	ARAN	10m	78	428	101	15	6	4	1	1	0
		100m	4	49	10	1	0	0	0	0	0
	<i>RoViIRI</i> 5 trips	10m	47	183	184	107	58	36	10	7	1
		100m	5	23	23	13	0	0	0	0	0

From Table 6.4, one can clearly see that the *RoViIRI* values for Deurninge - Enschede (N73) road on aggregated measurements of 40 trips of Audi for 10m profile is close to the one from ARAN. A closer look at the graph shows the strong similarity between IRI and *RoViIRI* values for different setup configurations. Figure 6.6 shows results of *RoViIRI* calculations and its comparison with IRI from ARAN for 10m and 100m profiles, pink ribbons show the segments for which the calculated *RoViIRI* value is the same as IRI but slightly shifted in right or left. Figure 6.6.1 shows the average calculated *RoViIRI* for 40 day rides by Audi A4 equipped with MotoG smartphone on the windshield. Figures 6.6.2-4 show the average calculated *RoViIRI* for 2 rides with 3 different cars with mounted MotoG on the windshield. It is obvious from these figures that our approach is very robust and our independent self calibrating process is very reliable. Figures 6.6.5-6 prove our claim of robustness as the data used for these Figures come from the same trip as data used for Figures 6.6.2-4 but smartphones were not mounted on the windshield. They were rather placed on the seat or glove-box.

Figure 6.7 shows that it is possible to classify road segments based on their calculated *RoViIRI*. Furthermore, continuous analysis of *RoViIRI* trend in time can help in detecting road deterioration. *RoVi* measurements show that cal-

Figure 6.6: IRI calculated for 10m and 100m profiles reported by ARAN and calculated as *RoVi-IRI* for different vehicles, smartphones, and configurations. Dashed line shows the road segment on which vehicle comes to a stop and the signal to noise ratio is too low to obtain an optimal value.

Figure 6.7: IRI for 10m profiles obtained from ARAN and *RoViIRI*. The discrepancy shown on the grey bars is due to the road deterioration since the last measurement .

culated *RoViIRI* for certain AI segments does not match which IRI because the road deteriorated further during the period from last ARAN measurements and the left lanes were already repaired.

6.4.3. Experimental setup - PostNL measurement campaign

During the dates between November 8th to December 4th 2016, for a duration of four weeks, conducted a road roughness measurement campaign. The measurements are performed by using smart mobile phones (smartphones) attached with a holder on the rigid place inside the vehicle, usually the windshield of the vehicle. The measurement consists on collecting the data of the vehicle on the road using smartphones sensors such accelerometer, gyroscope, magnetometer, GPS location. An app installed on the deployed smartphones collected the data from all the available sensors found on the smartphone. To reduce the user interaction and driver distraction and reduce the volume of the data, the data collection app uses a smart mechanism to collect the data only when the engine is turned on, the phone is plugged in and the vehicle is moving faster than a threshold speed t_s . The reason for implementing this smart mechanism is to collect only the data related with the road input and reduce the risk of contaminating the data with other activities like opening/closing the door, getting out of the vehicle etc. Another reason is to reduce the volume of the data when the vehicle is not moving and the postman is outside for a delivery. Figure 6.8 shows a snapshot of the running app, the mounting and usb connection.

Figure 6.8: Smartphone application, mounted phone and usb power connection

The measurements were conducted with different PostNL vehicles. Some of them being Volkswagen Caddy Max and others bigger commercial vans. The drivers conducted the measurements in unsupervised mode, driving relaxed as they would do in their everyday conditions. There can be conse-

quences in this driving mode, as the drivers following their natural instinct, especially when they are very familiar with the road they are driving on, will skip the anomalies on the road surface i.e. bumps, manholes, potholes and so on. This can lead to lower roughness indicators as compared with ARAN vehicle that measures the full profile width.

The measurements were conducted using Huawei smartphones from PostNL. The smartphones had an active data connection to facilitate fast geo-location acquisition. All the data are stored in an external SD-Card of 32 GB. The phone has only an accelerometer sensor sampling at a maximum sampling rate of 150 samples per second. gyroscope and magnetometer sensor were absent. In absence of gyroscope data, the driver behavior algorithm cannot be used to infer the bad road segments. Thus, some segments may have a different roughness compared to ARAN. The campaign covered a wide regional area of the Gelder-

Table 6.5: Distances traveled

Week Nr	Total Length (km)
Week 1	1.838
Week2	2.415
Week3	2.085
Week4	2.432
Total	8.770

land Province in the Netherlands. Table 6.5 shows the distances covered for each week and overall. Should be mentioned that the first week less data were recorded as drivers became familiar with the platform.

To set the results in a context of comparison with state-of-the-art methods, like ARAN IRI roughness index, information about the recent roughness index for the Gelderland Province are obtained from the province. ARAN measurement are recent ones, conducted from 6th - 9th of April 2016. In total they cover 138.8 km of lane road as shown in Table 6.6. Figure 6.9 shows the in-

Table 6.6: ARAN Measurements

Road	'N224'	'N225'	'N233'	'N304'	'N310'	'N781'	'N800'	'N801'	Total
Length	24.65	11.94	4.05	26.09	46.37	3.82	10.24	11.64	138.8
Overlap	5.11	0.01	1.08	9.01	17.66	3.76	6.85	8.69	52.17

spected road network by PostNL and ARAN vehicles. As shown by the figure the overlap segments are in total 57km. Another aspect to emphasise is that during measurements by PostNL, there was not a precise objective which roads or lanes to monitor and/or give importance to certain road segments.

6.4.4. Road roughness index - PostNL campaign

Comparison of the roughness calculation between ARAN and RoVi is performed by computing the RMSE between two measurements, considering the ARAN

Figure 6.9: Inspected roads by ARAN and PostNL vehicles

data as ground truth.

Figure 6.10: Profile segments calculated by ARAN and RoVi

As shown in Figure 6.10, it is difficult to do a sample by sample comparison between segments, as there are shifts and overlaps between ARAN and RoVi measurements. Road Roughness is computed on 10m length segments of road. Figure 6.10 shows the segments created by the ARAN vehicle and segments generated by PostNL-RoVi measurements. Because measured with consumer grade GPS chips of smartphones, segments generated by RoVi do not necessarily fall on the same span of ARAN segment. However, the accuracy of the segment is quite high as shown in the comparison Table 6.7: Table 6.8 shows the calculated RMSE in different flavors, where the normalized RMSE shows how well the estimation fits the ARAN measurements. It is interesting to notice that in Week 4 the results do not follow the trend of previous weeks, and this has to be investigated by asking the drivers if they followed the same lane as previous weeks or other factors contributed for this discrepancy.

Table 6.7: Profile segment length

	Mean	Standard Deviation	Max	Min
ARAN	11.6 m	10.6 m	22.59 m	5.4 m
RoVi	11.1 m	10.7 m	22.76 m	8.1 m

Table 6.8: RMSE between RoVi and ARAN Results

	RMSE		Normalized RMSE(mean)	
	10m	100m	10m	100m
Week 1	0.7279	0.4926	0.6302	0.4926
Week 2	0.7258	0.5387	0.6379	0.5387
Week 3	0.7961	0.5744	0.6418	0.5744
Week 4	1.0474	0.7500	0.7125	0.7500
Average	0.8244	0.5890	0.6557	0.4683

Table 6.9 shows the number of profile segments detected for each IRI category. For 10m length profiles the distribution of RoVi measurements is close to the distribution of ARAN vehicle measurements. The majority of the segments fall in IRI 0-1 and 1-2 bins, with around 500 segments more detected as category 1 in RoVi. The reason for this might be the way IRI is calculated by RoVi algorithm, where the values are averaged after each new addition is rounded up. When compared the 100m profiles, RoVi detected the majority of the profiles belonging to the IRI bin 0:1. IRI for 100m profile is calculated as the average of ten consequent 10m profiles. RoVi calculated the majority of segments as IRI 1 thus, the average IRI for 100m profile is expected to be in the range of 1. RoVi qualifies roads in general as better ones. More likely because frequent drivers, as in the case of postmen, adapt their driving to avoid vibrating parts of roads. However, conclusions cannot be drawn as it is unknown the driver behavior on the road and the state of the road itself 7 months after ARAN measurements.

It was noticed that in road N310 passing through Harskamp, segments with IRI 3 to 9 were measured by ARAN whereas RoVi didn't measure anything similar. In fact RoVi measured a smooth road with IRI 1 to 2 maxing 3 as shown in the Figure 6.11. Drivers did not confirm any anomaly in that segment, and inspections of Google Street-view images taken at the same time ARAN inspected that segment didn't confirm the high IRI measured by ARAN.

6.4.5. Experimental setup - bike campaign

Bike experiment campaign took place for one month in the city of Enschede, the Netherlands. Four participants biking every day on their way to work attached the smartphones to the bike with a bike holder. The selected bike paths included a variety of situations and path types including unpaved forest paths, brick and tile paths, high speed bike lanes and road biking. Overall distance

Figure 6.11: ARAN and RoVi results on route N310

Table 6.9: Results per segment category

10m segments									
IRI	1	2	3	4	5	6	7	8	9
Aran	3135	1960	383	92	28	11	5	3	0
RoVi	3624	1645	279	48	19	3	0	1	0
100m segments									
ARAN	284	241	33	3	0	0	0	0	0
RoVi	481	72	8	0	0	0	0	0	0

covered for the whole period of the campaign is **674.41km**. Two type of mobile phones were used to record the data, MotoG and Samsung Galaxy S4 mini as shown in Table 6.3. All the participants differed on their cycling style and type of bicycles used. To further increase the knowledge and reduce uncertainties about these anomalous situations, smartphones were also programmed to automatically take picture every 10 sec of the path in front of the bike.

6.4.6. Road roughness index - bike campaign

We also used RoVi to calculate the roughness index of the bike paths. For doing so, we collected data about various bike paths for a period of one month by four daily cyclists using smartphones attached to the handle bar of the bikes using a commercial plastic holder. Our four cyclists biked normally on a variety of path types, starting from an unpaved bike path going through a forest area and continuing into fast intercity bike lanes.

Since no standard vehicle exists to measure roughness index of bike paths, we asked our four cyclists to observe their paths and report on any anomalous situation on them. Being acquainted with their paths, they were able to identify a set of anomalies and their approximate position.

During our data analysis, we noticed that having two thin bicycle tires driving on a narrow path introduces a high level of uncertainties about the path roughness. However, using continuous and redundant measurements of the same path measured over and over again, we were able to reduce the uncer-

Table 6.10: Bicycle profile detections

All point detection for each cyclist								
Cyclist	IRI							
	1	2	3	4	5	6	7	8
1	5856	8455	828	58	19	8	3	24
2	22591	2015	301	180	44	16	6	5
3	16743	4827	377	55	14	1	4	1
4	16743	4827	377	55	14	1	4	1
clustered measurements of all measurements from all cyclists								
	7204	3336	272	27	12	3	1	1

tainty bound of the measurements and our calculated roughness index. To calculate the roughness index of the bike paths, we applied our IRI calculation method as the one we used for roads. Table 6.10 shows number of detected profiles for each roughness index for each user as well as detected profiles for the clustered measurements (of all measurements of all users). We investigated every calculated roughness index greater than 3 and compared them with the pictures made by the smartphones and reports of our cyclists. We have noticed that IRI greater than 3 for bike path relates to anomalous situations such as speed bumps (raised road segments to force drivers to slow down), deteriorated tile-paths, and to rough terrain from unpaved paths. Pictures taken by smartphones confirmed that our calculated IRI corresponds, in most cases, to the situation on the ground.

6.4.7. Evaluation of railroad track geometry and monitoring indicators

The ground truth data for track geometry was collected using the UFM120, i.e., a measurement train capable of monitoring railroads for speeds up to 120 kmph. It measures a multitude of track parameters, including cant, twist, curvature, vertical and horizontal alignment. These parameters are calculated for different track lengths. UFM120 uses camera and lasers to calculate the gauge width.

Eight smartphones (4 MotoG and 4 Samsung S4mini) were placed in pairs (M,S). One pair was placed in front, one pair in the back, and one pair at each quarter of the length of the train. A point to mention is that during these experiments, receiving GPS signal in the train was a challenge. This was due to the narrow windows and the complete metallic enclosure of the train. Nevertheless, we did not face this problem with passenger trains, and were able to synchronize all the smartphones on the train using the initial GPS time and UFM's own GPS system. We compared RoVi's track geometry results *RoViTG* calculated based on the approach explained in Sections 6.3.1 and 6.3.2 on the data collected by the UFM120 in the following manner. We first calculated the cant and curvature for low frequency bands. While, cant has long wavelengths characteristics, twist is high frequency phenomena.

Overall, the correlation between curvature measured by UFM120 and the our calculated curvature is about 83%. Our calculated cant is comparable with the one from UFM. As cumulative distribution function (CDF) shows that all calculated cants fall into the reported values. Figure 6.12 shows our calculated

Figure 6.12: 100mm and 50mm cant measured by UFM and the mobile phones. Mobile phones measure the start and stop of the cant (shown by the long bars) as well as deviation on during of the cant (shown by the short bars)

cant based on data from all smartphones and its comparison with the cant reported by the UFM. Long bars indicate the points at which the train entered the cant (the first long bars) and left the cant (the second long bars). The calculation of cant is consistent for all smartphones measurements. The short bars indicate the deviations of cant during the super-elevation. We are also able

Figure 6.13: A spectrogram of the signal and a wavelet transformation.

to identify other anomalies (not related to the track geometry) in the signal. For example, as shown in Figure 6.13, it is possible to identify user interactions with the smartphones (i.e., when the user moves the phone) or when train enters or exits a station. However, as shown in Figure 6.14, RoVi not only does not fail in case of users interaction with the phone but also is able to identify

Figure 6.14: The cumulative distribution function (CDF) of the calculated cant values.

these interactions because of its smart processing approach of frequently (in both time and space) collected measurements, which lack the exact users interactions with the phone at the same time and location.

The cumulative distribution function (CDF) illustrated in Figure 6.14 shows that 80% of the calculated cant values correspond to the the cant values measured by the UFM. The other 20% relates to the presence of noise in the smart-phone data.

6

6.5. Summary

This chapter proves the power and potential of crowd-sensing for condition assessment of ground transport infrastructures. We show that huge amount of low quality smartphone measurements that are taken over and over again on the same infrastructure together with smart sensor analytic can provide the same results as the high-end measurement devices and vehicles.

We present RoVi, i.e., a smartphone-based framework for continuous monitoring of ground infrastructures. It offers maintenance engineers a pervasive tool to measure condition and health of roads, railroads and bike paths, in real-time.

We conducted extensive measurement campaigns on various infrastructure types using smartphones and evaluated RoVi performance for road's roughness index, track geometry index, and bike path's roughness index. We compared results obtained from RoVi with measurements of the state-of-the-art measurement vehicles (ARAN and UFM track geometry train) as well as cyclists reports. Our evaluations show that road roughness index calculated by RoVi is comparable with the IRI measurements of ARAN regardless of vehicle type and position of smartphone in the vehicle. When applied for railroad track geometry monitoring, RoVi calculates cant, twist, curvature, and vertical alignment of the tracks. Also these calculations are comparable with measurements of UFM track geometry train. Increasing the number of rides enables RoVi to report results closer to the ARAN and the UFM track geometry train.

7

Conclusion & future work

This research explored continuous transport infrastructure monitoring from a crowd-sourced based perspective, using ubiquitous smart-mobile devices.

The main concern of this thesis is to address the limitations of the platform both in accuracy and sampling rate and to reduced these uncertainties by developing adaptive signal processing algorithms, classification and clustering algorithms that focus on specific infrastructure features.

Another important aspect of crowd-based location reports, leading to localization errors and uncertainties, is addressed by introducing a MapMatching and Aggregation algorithm based on Delaunay Triangulation.

The research as a whole is presented in a form of a framework implementable on any smartphone device. The framework services and functionalities are capable of working as standalone applications or integrated in user defined applications or Infrastructure Management Systems.

This Chapter outlines the contributions presented in this thesis and elaborates on future research to be conducted on infrastructure monitoring.

7.1. Summary

The contributions provided by this thesis from the optics of crowd-sensing based transport infrastructure monitoring can be summarized as follows:

Contribution 1

A system for road transport infrastructure anomaly detection and classification.

In Chapter 5, we presented a system for road pavement anomaly detection, to deal with detection and classification of diverse pavement anomalies that affect both the driving comfort and vehicle health as well as being an indicator of pavement deterioration.

We focused on coping with 1) speed dependencies on sensor readings, that affect the anomaly signature in sensor data, 2) uncertainties introduced by driver behavior behind the wheel, 3) localization accuracy of the reported anomalies. We achieved these goals by implementing an algorithm that reduces the speed dependency on sensor data applying a demodulation technique. A wavelet decomposition method decomposes the data into different frequency bands and machine learning algorithms are implemented to create a generalized model capable of classifying the road anomalies into three different classes *i)* transversal, *ii)* mild, *iii)* severe. A novel detection algorithm is proposed for cases when the vehicle does not have a direct contact with the pavement anomaly. This is achieved by detecting the driver behavior on the road and coupling the detected swerves with the anomalies. The system is evaluated for different categories of road users such drivers and wheelchair users.

Contribution 2

A smartphone-based framework and associated services for determining transport infrastructure maintenance indicators.

In Chapter 6, we presented a novel system to calculate diverse transport maintenance indicators for different infrastructure typologies 1. roads, 2. railroads, 3. pedestrian paths. We showed that smartphone sensor data are capable of measuring wavelengths related to infrastructure geometry. A spatio-temporal transformation algorithm is proposed to convert the temporal signal into spatial information corresponding to the *state of the art* requirements. Adaptive filtering is implemented to extract only the frequencies related to the infrastructure wavelengths. The results are evaluated by comparing them with *state of the art* measurements conducted by ARAN vehicle and UFM120 track geometry measurement train.

Contribution 3

A fast and robust aggregation and visualization algorithm for data reduction of crowd sensing-based infrastructure monitoring application.

In Chapter 4, we proposed a map-matching and aggregation algorithm based on Delaunay Triangulation algorithm to deal with the problem of smartphone GPS accuracies and the huge amount of sourced data. The algorithm deals with the problem of finding the nearest location within a range for each of the sourced locations and updates that location with the new information received. This allowed us to reduce the GPS positioning error from *8m* to *1.5m* from the center of the infrastructure segment. This algorithm showed to be capable of generating infrastructure location maps even in conditions where the maps of GIS providers were not adequately updated. We showed that by aggregating low quality sensor data we can increase the overall accuracy and be comparable with the results of specialized vehicles equipped with *high-end* sensor devices.

7.2. Conclusions

The main focus of this thesis was to study the capabilities of low quality sensor data received from smartphone sensors to provide an accurate information about the state of transport infrastructure. In particular, we concentrated our efforts developing algorithms able to extract valuable information from noisy sensors and translate that information into meaningful infrastructure indicators. The main research question that was raised was:

How can, the information collected from smartphone sensors traveling over different transport infrastructures, be translated into meaningful and accurate quality indicators that are useful for both infrastructure engineers and infrastructure users?

This question can be formally answered by first answering the five sub research questions. This sub questions are answered revisiting the raised hypothesis and the contributions of this thesis.

Q.1. What is the nature of transport infrastructure anomalies, which sensors capture them best and how is the sampled sensor data associated with them?

To answer this question, we started from two hypotheses. First, despite the fact that the vibrations caused by the infrastructure irregularities and transmitted to the smartphone traveling inside the vehicle can attenuate by the damping structures of the vehicle, sensors can capture the wavelengths, signatures, and nature of these irregularities. Second, the driver behavior on the road can be translated into valuable knowledge about the state of the infrastructure. We validated this hypothesis by showing that smartphone sensors are in did capable not only of capturing and classifying anomalies on the infrastructure surface (Contribution 1). Accelerometer and gyroscope sensors can capture vibrations and rotations induced by infrastructure anomalies. Gyroscope drift can be reduced and useful turn angles can be calculated to infer driver behavior activities. We also showed that these sensors, when meet a certain sampling frequency requirement, can also capture infrastructure geometry wavelengths(Contribution 2).

Q.2. How to deal with uncertainties and errors associated with smartphone sensors?

This question is addressed with the hypothesis that the uncertainties introduced by the low quality sensors and GPS inaccuracies can be diminished by aggregating the results from multiple measurements over the same segment of the transport infrastructure. We proposed a digital signal processing method based on wavelet decomposition (Contribution 1) to filter and enhance the sensor signal and addressed the GPS positioning errors by introducing an aggregation algorithm (Contribution 3).

Q.3. How to reduce the impact of speed on the quality of sensor measurements?

When consulting the related work and conducting the data collection campaigns we faced the influence of speed on sensor data. We started with the hypothesis that the speed of the vehicle probe modulates the sensor measurements in frequency and amplitude. To this mean we developed a method to mitigate the speed dependency on sensor data by demodulating the sensor signal using the envelope demodulation technique (Contribution 1) inspired by the Hilbert-Huang transformation method.

Q.4. What techniques are needed to efficiently process the sampled smartphone data and to translate them into accurate and reliable maintenance indicators?

This question is addressed by the hypothesis that using the state of the art signal processing and machine learning techniques, the vibrations and rotations of the vehicle caused by the infrastructure irregularities can be classified into corresponding anomalies on the infrastructure geometry. Based on this hypothesis we proposed a spatial based analysis method that converts the temporal frequencies into spatial frequencies to identify the infrastructure wavelengths. The characteristic of this wavelengths are used to compute maintenance indicators according to the infrastructure maintenance requirements (Contribution 2)

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Q.5. How to efficiently combine and represent the results from each individual smartphone into precise geo-location on the transport infrastructure?

This work started with the awareness of limited capabilities offered by the smartphone sensors. However, we addressed this challenge with the hypothesis that the uncertainties introduced by the low quality sensors and GPS inaccuracies can be diminished by aggregating the results from multiple measurements over the same segment of the transport infrastructure. This hypothesis was validated by showing first that the processed sensor data is comparable with the state of the art measurements and secondly by introducing an accurate aggregation algorithm that aggregates the data based on their geo-location within a certain range less than the average error of the GPS sensor. This allows us to aggregate together only the data that belong to that specific location. We evaluated our approach with large scale measurement campaigns conducted by PostNL vehicles and comparison with ARAN vehicle results. Thus, significantly increasing the aggregation accuracy (Contribution 3).

In conclusion this thesis offers to the research community insights on capabilities of smartphones to perform complex and quality sensitive tasks such the Transport Infrastructure Monitoring, when placed in the context of crowd based sensing and computation perspective. It also describes and provides a

useful framework to be used within this context. This thesis emphasizes the fact that *every information is good information* and capable of generating new information and knowledge.

7.3. Future Research

This thesis showed the potential of smartphones to conduct real time continuous infrastructure monitoring and paved the road for future research achievements and improvements. In what follows we will discuss some interesting research issues to be explored in the future:

7.3.1. Prediction models and deep learning

The results of our framework indicate the health of the infrastructure. However, the huge amount of collected information can be used to build prediction models based on deep learning algorithms to predict the future state of the infrastructure. This will be particularly useful to maintenance agencies as they based on this information can prioritize the maintenance strategies, funds and human resources as well as significantly reduce the maintenance costs.

7.3.2. Safety evaluation

In this thesis the driver behavior is considered only as tool to detect road anomalies. The proposed algorithm has potential to grow in other directions such the detection of hazardous situations in the driveway as a result of natural or construction deficiencies. Detection of aggressive or careless driving as a tool for Insurance companies. In the railway industry the angle calculation functionality needs to be further explored in terms of relationship of carriage, passenger load and cant deficiency.

7.3.3. Privacy

A key aspect that compromises the deployment of crowd-based applications is the user privacy. This is particularly important when the application involves the geo-location information. Since geo-location is an important feature of transport infrastructure monitoring privacy concerns need to be addressed.

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SpinSafe: Wheelchair Path Monitoring System

Movement and social life of wheelchair users are constrained by their disability and suitability of paths they can move on. Modern electric wheelchairs offer them assisted drive, making their movement easier and longer. They, however, do not prevent accidents, injuries, and inconveniences caused by path roughness and ramp slopes. Providing information about suitability and accessibility of paths and buildings for wheelchair users will enable them to beforehand plan their trip to not to be caught by surprises or not to take a trip all together. The recent emergence of smartphones equipped with inertial sensors offers new opportunities for provision of information regarding quality and accessibility of paths and buildings for wheelchair users. To this end, we propose a smartphone-based participatory system incorporating a hybrid unsupervised machine learning technique based on Self Organized Maps (SOM) to identify path conditions and to create clusters of similar path types. Our solution provides useful information about the angle of the ramp and curb slopes as well as pavement quality and roughness and path types.

Wheelchairs were first patented in USA in 1869, while the modern, lightweight, collapsible wheelchair we all know today, was invent in 1933. The majority of the wheelchairs do not differ much in construction. The main common features are availability of rear Φ 24" drive wheels and standard Φ 8" caster wheels, being foldable and lightweight for easy transportation, and being operated manually and/or motorized. Since their introduction they helped millions of people worldwide to have a more active social life. An estimated population of 1% in developed countries are wheelchair users¹. These individuals use wheelchairs due to several medical and physical conditions includ-

¹<http://www.newdisability.com/wheelchairstatistics.htm>

ing lower limb disabilities, Spinal Cord Injuries (SCI), head injuries, birth deformations and severe illnesses. Each condition necessitates the prescription of a special wheelchair setup. Although mobile, their locomotion is yet confined to places with appropriate paths. Authorities facilitate the mobility of the disabled users, including the wheelchair, by introducing rules and regulations considering path widths, curbs, ramp and slope angles, path pavement materials, etc [105]. While these regulations extend somehow the locomotion range, they still do not count for user conditions and situations. The scarce information regarding the pavement type, slopes and elevators, restricts prior planning for trips to be made by wheelchairs.

Wheelchairs are rolling vehicles prone to vibrations caused by the pavement roughness, varying in intensity and amplitude. From a mechanical point of view, they are simple rigid mechanical models, without springs, allowing the vibration to be transmitted all over the frame, including the user himself. This will expose certain categories of wheelchair users to collateral injuries. A SCI person should avoid Whole Body Vibrations (WBV) exceeding specific harmful levels that cause spasms [106]. The steep ramps and slopes can turn the wheelchair over. A trip through an improper pavement can cause the wheelchair to get stuck or even brake.

None of the existing navigational systems consider the route planning for wheelchair users. Previous research has utilized accelerometers to measure WBV and wheelchair vibrations for manual and motorized wheelchairs [58][59]. Conclusions from these studies indicate that wheelchair users are exposed to risks of secondary injuries from WBV. Cooper et al.[60] studied the effect of suspensions to reduce the shock and vibration on seat and footrest, founding that suspensions reduced the shock and vibrations, although they are not clearly superior to traditional designs. Attempts to reduce the WBV without compromising wheelchair features introduced new type of wheel constructions. Vornik et al. [61] compared these wheels in terms of vibration and spasticity for people suffering from SCI. They concluded that the new wheel type did not absorb or reduce the vibrations caused by path roughness. These studies indicate that accelerometers are capable of measuring the concerned vibrations induced by path roughness and the vibration level does not differ substantially among wheelchair models. The aforementioned works used different methods for data analysis. Frequency analysis was used by [60][59], Root Mean Square (RMS) of the vertical acceleration by [58][61], and variance analysis(ANOVA) by [61]. Although, wheelchairs are not equipped with accelerometers, their users use smart-phones equipped with GPS and inertial sensors. Accelerometers and gyroscopes are able to sense the vibrations and angular changes and smart-phones can handle, process, and share that information. This will allow wheelchair users to use and update that information in real time. They can measure the path roughness, ramp or curb angle, bumps, the presence of an elevator. They can safely plan their trip according to their needs, avoiding paths and directions not suitable for their specific condition. Based on this information we propose a smartphone-based system capable of sensing path rough-

Figure A.1: Wheelchair measurements over different type of surfaces. Wheelchair a) riding a smooth indoor surface, b) riding tiled with big gaps pavement, c) riding an unpaved but well pressed gravel pavement, d) entering a ramp

ness and reporting critical segments of wheelchair paths. Our system supplies the wheelchair users with valuable information by differentiating through different types of pavements, showing the level of vibration for each segment, and calculating the angle of ramps and slopes through the path. The system conducts signal analysis using Stationary Wavelet Transformation (SWT) for both accelerometer and gyroscope signals. The signal analysis is performed on the premise that different pavement anomalies generate different vibrations within certain frequency bins. The width of those frequency bins depends on some physical factors such diameter of the wheel, speed of the vehicle, damping characteristics of the physical system. Our field-test results demonstrate the capability and the precision of the proposed system.

A.1. Methodology

The front wheel called caster usually has a diameter of 8 inch and it is quite narrow to facilitate the propulsion of the wheelchair. The drawback of a small diameter caster is that it is prone to continuous vibration. A wheelchair driven on asphalt pavement will generate higher frequency low amplitude vibrations. Whenever the wheelchair drives on bricked pavement, low frequency vibrations will be generated corresponding to the frequency of the gaps between bricks on the floor. The speed of the wheelchair, as in all rolling vehicles, modulates the amplitude and frequency of those vibrations. At higher speeds the amplitude of the vibration for the same anomaly will be higher. Another factor to consider is the wheelchair construction, in a way that the two lateral sides are quite independent of each other. They act as suspension, and the sitting part with the rear wheels act as a dumper. Fig. A.1 illustrates a wheelchair, its accelerometer and gyroscope signals for different type of pavements for a 5 second ride. As it can be seen from Fig. A.1a, the max amplitude of vertical acceleration on a flat indoor pavement is $1.4m/s^2$ and the gyro angular velocity is $\omega = 0.2rad/s^2$. With the transition to a rougher brick pavement as shown in Fig. A.1b, the wheelchairs becomes more shaky and the amplitude of the vertical acceleration raises to $10.5m/s^2$ as well as $\omega = 0.5rad/s^2$. In the first 2

seconds, the speed is low and the spikes caused by the inter-brick gaps can clearly be observed. On an unpaved surface as illustrated in Fig. A.1c, the amplitude of vertical and lateral acceleration spike to 10.5m/s^2 and $\omega = 1\text{rad/s}^2$. When following a ramp as shown in Fig. A.1d, the roll axis of the gyroscope measures the angular change during the transition point of the ramp slope. Following this simple reasoning we can assume that by analyzing this axis of accelerometer and gyroscope we will be able to detect the pavement types, elevation as well as bumps and obstacles.

However, analyzing the signal in time domain is not enough as the signal is composed of different vibration elements that are modulated together. Also the pavements are not always as simple as shown in Fig. A.1. Most of the time, the paths are not flat, the surface gets more rough as it ages, the tree roots, manholes, sunken pavements make the surface uneven resulting in bumpy roads

A.1.1. Signal analysis and transformation

Frequency domain (FD) transformation allows us to analyze the frequency components of the signal. However FD is more suited for narrow band stationary signals.

The RoADS [?] uses Stationary Wavelet Decomposition (SWD) to decompose the sensor signals into 4 levels using Symlet sym4 wavelets. Wavelet decomposition provides an alternative way of signal processing, it has a good time and frequency resolution for both low and high frequencies, and is better suited for analysis of sudden and transient signal changes and analyzing irregular data patterns such as impulses generated at different time instances.

Considering the speed of the wheelchair to be at 6km/h or 1.7m/s and the sampling rate of the smartphone sensors to be at 60 samples/s, a 128sample window corresponds to a distance up to 3.2m , suitable to capture all the low frequency bumps on the path, the full anomaly can reside inside one window.

A.1.2. Learning and path classification

One of the main concerns of any classification is setting the ground truth and comparing the results with that. The algorithm should detect different types of anomalies. This is a rather challenging task, especially when aiming to implement it on smartphone platforms with limited energy supply and processing power. There are two approaches to the problem of anomaly detection, i.e., *i*) supervised learning and *ii*) unsupervised learning. The first approach relies on the premises of knowing beforehand the classes to be classified. Using a handful of data representing those classes, a classifying algorithm can be taught to distinguish between them. Then performance of the algorithm is tested using unknown data sets by manually checking the results. The alternative approach is the unsupervised learning method. The method tries to create clusters of data with similar attributes. Choosing the right method depends on the task and the complexity of the data to be classified.

Taking all these into consideration, we decided to use unsupervised ma-

Figure A.2: Typical visualisation of Self Organizing Maps

chine learning techniques, namely the Self-Organizing Map (SOM) Neural Network [95][101]. The SOM algorithm is based on unsupervised, competitive learning. It is appropriate for clustering problems, i.e. grouping different elements according to the similarity in pattern and feature set. SOM is inspired by the way the brain stores and organizes the information, by storing the correlated information in close by area. SOM creates a bi-dimensional map of neurons in which the input features are grouped through a neighborhood function that calculates the degree of similarity between them. Features representing similar information will be closer on the neuron map. Fig. A.2 shows a typical visualisation of a SOM neuron network lattice. The features are recursively shown to each of the neurons. The neighbourhood is characterized by the distance between neurons. Dark colors represent longer distances, the distance is the difference between the pattern features. We can summarize the behavior of a SOM network in the following steps: Consider a feature set D , the feature n belonging to D^i , where i is the index of the feature vector. The algorithm calculates the Euclidean distance of $D^i(n)$ and the weight W of the neurons v . The neuron that produces the shortest distance is called Best Matching Unit (BMU) and is indexed u . The BMU has neighbour neurons. Neighbourhood radius is restrained with a neighbourhood function $\Theta(u, v, s)$. Both BMU and neighbours are updated giving them a weight closer to $D^i(n)$ as following:

$$W_v(s+1) = W_v(s) + \Theta(u, v, s) \alpha(s) (D^i(n) - W_v(s)) \quad (\text{A.1})$$

, where s is the current epoqe to be no more than a limit denoted by λ .

This way a high dimensional space can be mapped into a plane. SOM property of *topology preserving* means that feature vectors preserve their relative distance also into the plane, ie. feature vectors that are close to each other in the input space are mapped to nearby neurons in the SOM. This property allows SOM to serve as a clustering tool for high-dimensional data. The SOM network has also a generalization capability, recognizing features never seen before, by assimilating the feature within the neuron it is mapped to.

Based on aforementioned analysis, the extracted features from accelerometer sensor axis will create a high dimensional feature space with enough information to contribute on clustering together similar patterns. The SOM is trained with the collected data and the formed cluster are manually compared with the known path segments transforming the clusters into labelled classes.

A.1.3. Ramp and curb angle calculation

Wheelchairs are quite narrow vehicles and their center of gravity is also quite high, making them subject of accidents when passing through steep ramps and curbs. Although rules and regulations sanction the safety parameters for the slope, they cannot satisfy all the cases. For the safety of the wheelchair user, a slope should be at least with a ratio 1:12 corresponds to an angle of $\approx 5^\circ$. In [65], a method to calculate the angle of the turn using gyroscope Yaw axis was introduced. We use the same method to calculate the slope angle of the gyroscope Pitch axis and also the angle of the curb using the information from Roll rotation. When the wheelchair enters a ramp, a rotation on the lateral axis, i.e., Pitch axis, is registered. The gyro signal changes at the slope and at that precise moment the algorithm starts the integration of the angular velocity, using the smoothed signal from mean of the windows. If the angle at the peak of the signal is less than 1.5° , the integration is dropped as the slope is not too steep. This way all slopes more than 3° can be precisely detected.

A.2. Evaluation

We evaluate performance of our wheelchair path monitoring algorithm empirically through experiments. The experiments were conducted in two different geographical places. Table A.1 gives an overview of the experimental setup. Two motorized wheelchairs operated by their experienced users collected data in motorized and manual mode in different urban and indoor paths in Singapore. Two manually operated wheelchairs were used to collect data at the campus of the University of Twente in Enschede the Netherlands. We perform the experiments at least twice for each path.

A.2.1. Experimental setup

The selected paths were chosen in such a way to include all types of terrains possibly a wheelchair user will usually pass through. This includes asphalt, bricked sidewalks, wooden and metallic bridges, ramps and slopes, elevators, manholes, and curbs. The trips in Singapore experiments contain video footage

Table A.1: Experimental setup

Inventory	Singapore		Netherlands	
	Mounted sensor			
	MbientLab Metawear		None	
Acc	50 Hz			
Position	Center frame			
	Smartphone			
	Samsung S4	Samsunge Note 3	Samsung S4 mini	Motorola Moto G
Acc	92Hz	50Hz	75Hz	97Hz
Gyr	92Hz	50Hz	135Hz	185Hz
Position	armrest	carried	armrest/carried	armrest
	Wheelchairs			
Model	Yamaha JWX-1	Merits P201	Unknown	Unknown
Propulsion	Electric/Manual	Electric/Manual	Manual	Manual
Main Wheel	24" pneumatic	14" foamfilled	24" pneumatic	24" pneumatic
Caster	8"pneumatic	8" foamfilled	8" pneumatic	8" pneumatic
Speed	6 km/h	6.4 km/h	6.5 km/h	6.5 km/h
Weight	14.7 kg	78 kg	<10 kg	<10 kg
Nr. Trips	3	2	13	7
Photo/Video	Video	Video	Photo 1p10s	Photo 1p10s
Distance	6.3 km		20 km	

recorded by the smartphone's back camera and two of the trips were labelled. The wheelchairs were fitted with an accelerometer (fixed at the center of the frame) and two smartphones (one fixed with a holder to one side of the wheelchair armrest and the other one on the chest of the user). Experiments in Singapore were performed in indoor shopping malls and the paths surrounding them. Experiments with manual wheelchairs at the university campus were performed using two smartphones, one fixed on the side of the wheelchair armrest and the other laying on the seat between the legs of the user. Photos of the path ahead were captured every 10 seconds. These experiments were conducted in outdoor environments, covering different scenarios ranging from asphalt, brick paths, gravel paths, bridges, parks etc.

A.2.2. Data preparation

The linear acceleration, i.e., the acceleration signal without the gravity component, and the gyroscope signal for their respective three axis were collected with the highest possible sampling rate allowed by the Android OS. The GPS signal were sampled with 1 sample per second. The data was windowed in segments of 2 seconds with 2/3 overlap. The signal was decomposed through STW at four levels of decomposition with a sym5 wavlet. The following features were extracted for all levels of approximations and details:

- mean
- mean absolute deviation
- standard deviation
- variance

Figure A.3: The signal from Fig.A.1 clustered with SOM 16 nodes above and 25 Nodes below. a) riding a smooth indoor surface, b) riding tiled with big gaps pavement, c) riding an unpaved but well pressed gravel pavement, d) entering a ramp

- RMS
- energy

The overall feature set per window consists of 288 features. Because the SOM calculates the Euclidean distance between the features, the feature vectors were normalized to have an Euclidean distance of 1:

$$x'_i = \frac{x_i}{\sqrt{\sum_i^n x_i^2}} \quad (\text{A.2})$$

A.2.3. SOM evaluation

The appropriate dimensions for the neuron lattice is determined by training the SOM with different dimension parameters and feature sets. The aim is to find a specific number of neurons that sufficiently detects the path segments. The performance of each SOM dimension is tested on a set of labelled data. Fig. A.3 shows the results of clustering for the four states shown in Fig. A.1 using a 16 (4x4) and a 25 (5x5) node SOM. By visual inspection of clustered neurons in the lattice of Fig.A.4, the tendency to create 2 distinctive clusters that do not belong to different anomalies but rather to the data collected by the carried and mounted smartphones becomes clear. The pattern of cluster formation is consistent with the one of 4x4 lattice as well.

We evaluate the performance by first of all identifying the path segments and annotating their start/stop coordinates making them partially labelled segments (the type of path is known but not any particular bump). KML files are generated for each trip and each class of the trip with segment number. The results for each segments show how many data windows are mapped to the neurons representing that path type for both mounted and carried smartphones. The KML files are mapped on the Google Earth and the correctly clustered segments are counted. This procedure is repeated for different lattice dimensions.

Figure A.4: SOM neighbor distances for 4 different neuron lattices. The light coloured distances correspond to the created cluster of neurons in a neighbourhood.

Figure A.5: Slope angle distribution

Figure A.6: Speed histogram

A higher dimension of neurons will create more defined clusters. Even though during the experiments we tested different combination of lattices up to lattices of 10x10 neurons, for evaluation simplicity we decided to use a 25 node SOM.

Fig. A.8 shows results of clustering procedure for the data collected in Singapore. It can be seen that data is clustered into brick paths, small bricks and asphalt, and mild bump anomalies. The video footage shows that experienced wheelchair users are cautious, always following safe paths, although they were instructed to collect more rough path segments. Another important reason is that experiments took part in indoor or semi indoor facilities. Nevertheless the user were perfectly satisfied with the results. Fig. A.7 shows results of clustering procedure for the data collected in the Netherlands. It can be seen that results are more diverse as more possible paths outdoors were covered in the experiments.

The severe bumps, bridges and other severe anomalies are detected by both mobile phones, i.e., carried by the user and mounted on the seat of the wheelchair. One may note that the signal from the carried phones are clustered by other neurons, not related to the neurons responsible to cluster data from mounted phones. We observe that the 3x3 SOM lattice was not able to classify correctly all the path events. The results are inconsistent and not correlated.

A.2.4. Slope angle calculation

The slop angle is calculated with the algorithm described in Chapter 5, replacing the Yaw with the Pitch axis of the gyroscope. Fig. A.5 shows calculated angle distribution for detected slopes more than 2° over all experiments. The wide slope angles above 5° are not physical slopes but user interaction with the wheelchair. The wheelchair can incline backward when the big wheels are rapidly turned backwards. This is usually done when the user wants to pass an obstacle in front of him. The calculated angle was consistent for both mounted and carried smartphones.

Figure A.7: The results in UT Campus

Figure A.8: Singapore neighbourhood

A.3. Summary

We presented a system that helps the marginal category of wheelchair users to conduct a more active and safe lifestyle, by allowing them to monitor in real time the paths they drive on. The proposed system is based on the ability of the Self Organized Maps (SOM) to divide the smartphone collected sensor data features into clusters corresponding to different path pavements and path anomalies. Performance evaluations are done using different scenarios with smartphones mounted on wheelchairs and carried by the users, on different path types, on smooth indoor floors and rough outdoor pavements, and with different wheelchair types. Our experimental results show that our system is able to correctly detect dangerous situations related to steep ramps and curbs by calculating the Pitch and Roll angle of the wheelchair in these situations. SOM unsupervised learning algorithm and the SWT wavelet decomposition proved to be great tools for clustering and classification of the non-stationary signals, like the ones collected by mobile phones.

About the author

Fatjon Seraj

Fatjon Seraj was born in Vlore, Albania in July 11, 1977. He graduated from "Ali Demi" high school, Vlore, Albania in 1995.

He received his Bachelor of Science (BSc) degree in Automated Systems Engineering from Kiev International Aviation University, Ukraine, in 2000.

In 2001 he obtained a Master degree in International Business Administration (IBA) from National Aviation University, Kiev Ukraine.

He received his Master of Science (MSc) degree, in 2002, in Computer Engineering. The topic of his research was on creating a flight simulator algorithm for the *Tupolev TU 154* aircraft, that can be easily deployed into the university cockpit simulator facilities.

Before starting his doctoral studies, he had an extensive work experience in academic, public administration, finance and industrial sectors.

His professional interests focus on digital signal processing, crowd-sourced data generation, BigData and artificial intelligence algorithms as well as development of these systems.

List of Publications

1. F.Seraj, B.J.M. Vander Zwag, A.Dilo,T.Luarasi and P.J.M.Havinga "RoADS: A road pavement monitoring system for anomaly detection using smart phones." In: *Big Data Analytics in the Social and Ubiquitous Context. Lecture Notes in Computer Science 9546. Springer Verlag, Berlin, pp. 128-146.*
2. F.Seraj, K.Zhang,O.Turkes,N.Meratnia and P.J.M.Havinga "A smartphone based method to enhance road pavement anomaly detection by analyzing the driver behavior." In: *Adjunct Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2015 ACM International Symposium on Wearable Computers, 07-11 Sep 2015, Osaka, Japan. pp. 1169-1177.*
3. O.Türkes, F.Seraj, J.Scholten, N.Meratnia and P.J.M.Havinga "An Ad-Hoc Opportunistic Dissemination Protocol for Smartphone-based Participatory Traffic Monitoring." In: *Proceedings of the 82nd IEEE International Vehicular Technology Conference (VTC Fall 2015), 6-9 Sep 2015, Boston, MA, USA. pp. 1-5. IEEE Vehicular Technology Society.*
4. F.Seraj, P.J.M.Havinga and N.Meratnia "SpinSafe: An unsupervised smartphone-based wheelchair path monitoring system." In: *Proceedings of the IEEE International Conference on Pervasive Computing and Communication Workshops, PerCom Workshops 2016, 14-18 March 2016, Sydney, Australia. pp. 1-6. IEEE Computer Society.*
5. F.Seraj, N.Meratnia and P.J.M.Havinga "RoVi: Continuous Transport Infrastructure Monitoring Framework For Preventive Maintenance." In: *Proceedings of the IEEE International Conference , PerCom 2017, 13-17 March 2017, Kona, Hawaii, Big Island. pp. 1-6. IEEE Computer Society.*
6. F.Seraj, N.Meratnia and P.J.M.Havinga "An aggregation and visualization technique for crowd-sourced continuous monitoring of transport infrastructures." In: *Proceedings of the IEEE International Conference on Pervasive Computing and Communication Workshops, PerCom Workshops 2017, 13-17 March 2017, Kona, Hawaii, Big Island. pp. 1-6. IEEE Computer Society.*

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