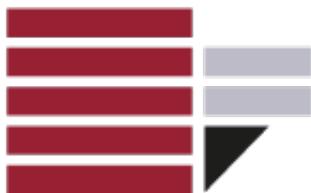


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MONITORING ROAD SURFACE
CONDITIONS USING IMU

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Abstract

In this work, we examine how to improve traffic safety through collecting and distributing road surface condition information using cheap sensors, in order to provide useful information for road travelers and public institutions for road network maintenance. A system to measure indexes like the International Roughness Index (IRI), and the location of critical points on the road surface, has been developed. The description regarding the quality of the road surface is carried out through the analysis of a longitudinal profile. In particular, a smartphone was used for the purpose, located inside the car, and from which data produced by main sensors, such as the accelerometer and the GPS, are both collected and processed. ProVAL (Profile Viewing and AnaLysis) software was used to calculate the final result of the IRI, while MATLAB (Matrix Laboratory) modules were processed to calculate other indexes and a first part of IRI evaluation. The obtained results are displayed on an interactive map using the Mapbox APIs, it is possible view and select one of the indexes, and get informations (such as the associated value) for each point displayed on the map. Regarding the indexes, the obtained results for the IRI shown that there is a good relationship between the values associated with a given road segment respect IRI scale, even though it was not possible to create a correlation equation but it was just simulated, while the critical point identifies the most damaged points on the road pavements that are within specific thresholds. Eventually, future integration of the system will be proposed and discussed.

Abstract

In questo lavoro, verrà esaminato come migliorare la sicurezza stradale, tramite la raccolta e la distribuzione di informazioni relative alle condizioni della superficie, attraverso l'utilizzo di sensori a basso costo, al fine di fornire informazioni utili, sia agli utenti della strada che alle istituzioni pubbliche per la manutenzione della rete stradale. È stato sviluppato un sistema per la misurazione di alcuni indici, quali l'International Roughness Index (IRI) e la localizzazione dei punti maggiormente critici. La descrizione della qualità della superficie stradale è stata condotta mediante l'analisi di un profilo longitudinale. In particolare, a tal fine, è stato utilizzato uno smartphone, correttamente posizionato all'interno dell'abitacolo, dal quale vengono registrati e processati i dati prodotti da alcuni sensori principali come l'accelerometro ed il GPS. Il software ProVAL (Profile Viewing and AnaLysis) è stato utilizzato per calcolare il risultato finale dell'IRI, mentre sono stati sviluppati degli script MATLAB (Matrix Laboratory) per il processamento degli altri indici e per il calcolo iniziale dell'IRI. I risultati ottenuti vengono visualizzati su una mappa interattiva, tramite l'utilizzo delle API Mapbox, in cui, oltre a visualizzare i risultati per ciascun indice, è possibile ottenere delle informazioni da ciascun punto (come il valore associato) cliccando su di esso. Per quanto riguarda gli indici, i risultati ottenuti mostrano che l'IRI ha una buona relazione tra il valore che è stato calcolato per un determinato segmento stradale e la sua scala di riferimento (IRI scale), nonostante non sia stato possibile identificare un'equazione di correlazione, ma è stata solo simulata. Invece, per quanto riguarda l'indice dei punti critici, esso identifica in modo accurato i punti maggiormente danneggiati della superficie, che ricadono all'interno di determinate soglie. Infine, gli sviluppi futuri del sistema verranno proposti e discussi.

1

Introduction

The monitoring of the conditions of a road surface, such as the detection of anomalies associated with it, like potholes, bumps, joints, level passage, small covering defects, breaks, and theirs proper locations helps to improve road users' safety, from pedestrians to drivers and has a significant impact on the road maintenance. In fact, an adequate mapping of the road infrastructure can allow workers to intervene at the most critical points, or at the most disadvantaged sections of the road itself. For this reason, in order to offer a continuous efficient and up-to-date service, it is very important both to inform road users about the road surface quality and to obtain information from them.

The accurate evaluation of the quality of a road surface is a critical issue: transport system could become more efficient, comfortable and, most of all, safer. In fact, the presence of different types of anomalies on a road surface can make the transport-related energy efficiency worse, by increasing fuel consumption, a decay of suspensions and brakes. Crossing one of these anomalies both generates vibrations inside the tires' and suspensions' system, and affects the deformation of the tire, causing energy leaks and increasing rolling resistance. In addition, an increased risk of major damage to the

vehicle (broken rims, tires puncture, or damage to the car body) can occur.

Road pavement monitoring is usually carried out through a variety of instruments, most of all various types of profilometers; however, especially in the most advanced cases, a profilography¹ can be used, too. Given the high cost of these instruments, the use of mobile technologies or cheap hardware sensors is widely adopted in this area, with the aim of providing to road users the opportunity to obtain real-time information about the road surface conditions and the traffic situation, or understand road accident cases promptly. All of that is made possible thanks to the hardware of these devices. In fact, if we mainly focus on smartphones and tablets, the majority of them uses a three-axis accelerometer to collect acceleration data, due to vehicle motion, and a GPS receiver to obtain location information of the current specific road segment.

This work focuses on the development of a system for the road surface conditions monitoring, that makes use of inertial measurement units (also known as **IMU**), electronic hardware systems based on inertial sensors, such as the ones in our smartphones/tablets or Arduino devices, which have much lower prices than the standard instruments used for this task. The system is based both on the reading of data collected through the smartphone, and on the post-processing elaborations of the GPS signal and acceleration data, (in which particular attention is given to vertical acceleration impulses, corresponding to **high-energy peaks** and possibly representing an "*anomaly*" of the road surface). After all the data has been processed, the following benchmarks for the road surface conditions are extrapolated:

- **IRI:** International Roughness Index: the international standard for road surface monitoring.
- **Critical Points:** an index that locates and labels the most critical points on the road surface.
- **Simple Acceleration Points:** an index able to interpret the variation of the acceleration signal on predetermined dimension segment of road travelled at different speeds.

The obtained results are shown on a web-site on an interactive map.

The Introduction Chapter discusses the main instruments(1.1) used for the road surface monitoring, like profilometers(1.1.1, page: 3), and the reasons why this system

¹The profilograph is a device used to measure pavement surface roughness

was developed (1.2, page: 9).

Subsequently, the Chapter2 discusses about the *IRI*, its history and its calculation.

Chapter3, talks about the Inertial Measurement Units (IMUs), specifying what they are, their functioning and physical principles, measurement accuracy, and how they are into smartphones.

Then, Chapter4 analyses how these data can be processed in order to get road surface conditions, what these data represent and why both a data filtering, through the analysis of the filter types that can be used to improve the processing, and a Fourier Analysis are mandatory for that purpose.

Chapter5 discusses the work that has been done, from the data-extraction through smartphones, to how the listed above indexes1, whose elaboration is also explicated, are displayed on the map. Eventually, the last Chapter6, is focused on the obtained results and on possible future extensions.

1.1 Road surface monitoring instruments

It is possible to identify two main instruments' families for the measurement of the longitudinal road profile: *static* and *dynamic*. The first ones perform the measurement of road profile by points, thus in a statical manner, while the second ones through a dynamic method, due to their movements at high speeds; in fact, during the detection period, the vehicular traffic could be high, for this reason reaching high sampling rates could remove the noise of vehicle traffic, caused by the detection operation itself. However, over the years, it was preferred to distinguish these families as indirect and direct instruments. The first ones are called *Response Type Road Roughness Measuring Systems (RTRRMS)* and measure the "effect", produced by interaction vehicle-pavement, in kinematic terms (displacement, velocity or acceleration). The second ones, called **profilometers**, return the sampled road profile for points within a defined range, instead.

1.1.1 Profilometer

Profilometers are capable of providing a digital profile of the road surface. Compared to RTRRMS, they can provide a more stable measure of road irregularities. In fact, the irregularity measures obtained by the RTRRMS systems are significantly affected by

the inertial and mechanical characteristics of the vehicles on which they are mounted. However, even the measurement made by the profilometers represents an approximation of the actual road surface profile[19].

ISO-Standard[1] identifies the following four fundamental properties to classify the profilometers:

1. **Instrument mobility:** For this property ISO-Standard[1] provides four distinct classes.

Mobile, high speed : refers to the vehicles equipped with profilometers which can be used at a test speed greater than or equal to 60km h^{-1} .

Mobile, low speed : refers to the vehicles equipped with profilometers which can be used at a test speed smaller than 60km h^{-1} .

Stationary in presence of traffic : placed directly on the road surface at the point you want to detect.

Stationary in absence of traffic : cannot be moved quickly from a measurement site, e.g: during the measurement on a site, that one will be closed to the traffic.

2. Detectable wavelength range:

According to ISO-Standard[1], five ranges are indicated for this property, each-one distinguished by a letter:

Classes	A	B	C	D	E
Wavelength range	0.05 to 0.16 mm	0.2 to 0.5 mm	0.63 to 2.0 mm	2.5 to 50 mm	63 to 500 mm

Table 1.1: Classification of profilometers according to ISO wavelength range

The wavelength allows understanding the type of a road pavement. In fact, the road surface, also called *texture*, is divided among four distinct categories: microtexture, macrotexture, mega-texture and irregularity. Referring to the wavelength parameters shown in the table 1.1, the texture categories fall in this wavelength range[19]:

Wavelength	0.5 mm	50 mm	0.5 m	> 0.5 m
Texture	microtexture	macrotexture	mega-texture	irregularity

Table 1.2: Texture class in function of wavelength

A profilometer can detect one or more wavelength classes.

3. Nature of instrument contact:

According to the nature of the contact between the used instrument and the road surface, profilometers can be classified in:

- **Contact Devices:** the sensor that executes the reading during the measurement, establishes a real physical contact with the surface that is being investigated;
- **Contactless Devices:** the reading sensors do not have physical contact with the road surface, therefore the height between the profilometer sensor and the road surface point is detected thanks to the projection on that point

The operating difference is substantial: the first has a direct contact with the road surface but it can not move at high speeds during the survey, which is the main prerogative of the second type, instead.

For what concerns the accuracy of the measurement, the profilometers have been classified by the World Bank[20] as:

Class 2 : devices that can make a random error during the survey;

Class 1 : very accurate devices: the possibility of measurements affected by a random error is extremely low.

Contact Profilometers

The Walking Profiler or Dipstick[14], thanks to its precision in determining road profiles, falls into the Class 1 (high precision profilometers) of the World Bank rating[20]; it is even often used to calibrate other equipment.



Figure 1.1: Examples of Walking Profiler (left) and Dipstick Profiler (right).

Contactless Profilometers

These profilometers are generally made up of one or more acoustic or electromagnetic sensors and mounted on a vehicle. Nowadays, laser is the most widely used sensors. Laser sensors are extremely delicate and expensive. A single-sensor detection, however, only provides the relative dimension of the sensor over the road surface (height between the profilometer sensor and the road surface point), which is not sufficient to know the road profile. So, generally, in order to obtain a point of the road surface itself from a higher point over the vehicle, an accelerometer is placed on the sensor structure, which provides, through a double integration, the displacements of the sensor itself in correspondence of the road surface.

The final goal of these profilometers is to extrapolate the IRI; that one, however, can not be detected only by one sensor, for the same principle of the IRI that discussed in the Chapter2.



Figure 1.2: Examples of contactless profilometers mounted on the vehicle.

4. Operating principle of the device:

The easiest way to classify a profilometer is its internal operating principle. According to this, four basic categories of profilometers were established[24].

Laser Profilometer Makes use of an appropriate filtering, which can distinguish laser light from the ambient light with an excellent contrast. Generally, a laser profilometer consists of two fundamental components:

- Source of Emission
- Capture-Transducer²

The operating principle of a laser profilometer is based on the optical principle of triangulation: the emission source projects a laser on the road surface, with a certain inclination angle to normal. The radius, diffused from the road surface, is received by the capture-transducer, which is also in an inclined position to receive the return signal. Then, the radius is transmitted through a lens to the transducer[5] (sensitive photo semiconductor). The capture-transducer source provides a signal D , as output data, proportional to the height h (the distance between the laser incidence point on the road surface and the emission source).

²A transducer is a device that converts one form of energy to another one.

Stylus Profilometer Represents the progenitor of all road surface monitoring instruments. It uses a pointed stylus, which touches the surface, and reads the small perceived irregularities, transforming them into other forms of energy. Then, an electric transducer transforms the mechanical movements of the needle into electric oscillations. These devices are equipped with a stylus needle, that is in a vertical position respect to the survey surface, which is lowered in order to physically touch the road surface. A transducer, mechanically connected to the needle, captures the magnitude of the vertical motion by transforming it into an electrical signal.

Light Sectioning Profilometer: Uses a light source to produce on the road surface a little line or a high band of light, with defined edges, on the road surface. A camera resumes this line of light with a certain inclination angle and with respect to the direction of the light. In the camera output, that consists of an x-z plane, the profile is represented by the contrast line between the illuminated area and the rest of the road surface. Generally, applying this kind of profilometers requires an high-resolution image management.

Ultrasonic Profilometer: Equipped with a mobile electro-acoustic sensor that emits and receives ultrasounds. These signals are first sent to the road surface, reflected and intercepted by a special microphone. The measurement is performed by considering the time between the transmission and the reception of the signal so that the distance between the ultrasonic source and the surveyed surface can be calculated[14].

1.2 Motivation

As can be seen above, the monitoring of the conditions of a road surface is a critical issue, very useful for travellers and maintenance institutions.

With regards to travellers, it is very important to know the conditions of the road they will have to travel and their level of "comfort": inside the vehicle, passengers perceive a certain amount of vibrations, strongly dependent on the suspension system associated with vehicle in question. To be able to improve the perceived comfort of road users is one of the aims of this work: travel comfortable road sections is better than travel the disadvantaged ones. Disadvantaged roads, in fact, increase the risk of car damages and of fuel consumption (according to some studies, a good floor pavement could improve fuel consumption by $\cong 2 - 6\%$ [12],[9]). Furthermore, in a constantly moving society like ours, the maintenance of roads becomes a central aspect of a municipal administration. The bad maintenance of the road surface has consequences not only on the safety and health of the drivers but also on the decor of the Commune itself. The investment that year after year the municipal authorities make for the viability are very low. And according to [17], only a few of the major Italian municipalities can exceed a spending average pro-capite of €100,00. So, having an effective monitoring system would help both drivers and organisations, thanks to a more efficient maintenance of the critical issues related to the roads. However, the main matter is what tools have to be used in order to carry out the monitoring. In the previous section (1.1.1), in fact, we have analysed the profilometers, which are able to directly measure the quality of the road profile, but their cost is very high and only a very small number of people can make the surface monitoring. Thus, in this work only low-cost inertial measurement systems are used, such as the sensors of mobile devices, which, nowadays are owned by the majority of drivers, who could be able both to get almost effort-free road quality information and to actively participate in the collection of data.

2

International Roughness Index

The International Roughness Index (IRI) [18], was introduced in 1986 by The World Bank([18], [21]). It represents the most used road roughness index to evaluate and manage road infrastructure.

IRI is defined as the ratio between the sum of vehicle-wheel displacements of a standard vehicle, travelling at 80 km h^{-1} along a roadway[20]. It is calculated using the "*quarter-car*" mathematical model, whose response is accumulated in order to produce a roughness index[14] with slope units (in mile^{-1} , m km^{-1} etc...) The measurement of IRI is required for all the data provided to the United States Federal Highway Administration, and it is covered by several standards from ASTM International, such as the ASTM E1364 - 95 (2005)[2]. In addition, the IRI is also used to evaluate a new pavement construction, i.e. to determine penalties or bonus payments based on its smoothness.

2.1 History

In the early 1980s, in the United States of America, some highway engineering companies identified the road roughness as the main index to determine the level of comfort of a road network used by different road users, from pedestrians to driver. There were already some methodologies used to determine the roughness at that time, however, they were different among the various agencies and neither reproducible or stable over time. For this reason, the United States National Cooperative Highway Research Program (NCHRP) started a research project in order to help the state agencies to improve the utilisation of their own methodology for evaluating the road roughness[10]. The project was then continued by The World Bank[18] under the name of ***International Road Roughness Experiment*** (IRRE)[22], whose main goal was to determine a way to compare or to convert the data obtained from different countries, all involved in The World Bank's projects. After several studies, the results showed that the majority of used methodologies and instruments were able to produce significant measurements[21] of road roughness. Thus, all those methodologies were standardised and the measurement was referenced to a single, common scale. Sayers and Karamihas[14] proposed a scale, shown below, where the IRI level is related to the characteristics of a surface and to its degradation. This scale, whose name is International Roughness Index (IRI), was, in fact, first defined and then tested only for this purpose.

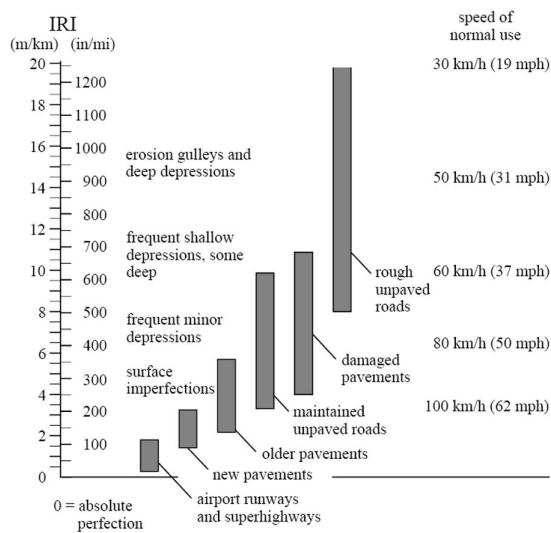


Figure 2.1: International Roughness Index Scale defined by Sayers and Karamihas [14]
Representing the characteristic of road roughness in function of IRI.

2.2 Definition

IRI is defined as a mathematical model of a bidimensional road profile. This road profile represents the vertical elevation of the road surface as a function of the longitudinal distance along the travelling distance[25]. So, its aim is to show how the elevation varies depending on the length of the road in question. The roughness measurement is difficult and complex because it depends on the vehicle characteristics and the suspension system, and also from the actual road pavement conditions. It can be calculated from profiles that are obtained by any valid measurement method, such as high-speed inertial profiling systems. The Quarter-Car mathematical model replicates road roughness measurements that were used by highway agencies between 1970 and 1980. The IRI is statistically equivalent to the other already-in-use methodologies, i.e. the correlation between the IRI and any type of RTRRMS, is as good as the correlation between two RTRRMS measurements.

"IRI has the advantage of being repeatable, and stable over time." IRI scale has been chosen for compatibility with previous measures of the roughness.

The frequency content of the movement of the suspension is very similar to the frequency content of the vertical acceleration of the chassis: a very important correlation. In fact, the overall level of vibrations is similar to the overall load level of vibrations of the pavement and, despite the IRI is not suitable for the calculation of all types of vehicles, the results between these two types of data collection are almost equalled, thanks to that correlation. Furthermore, this type of correlation is crucial both to demonstrate that this index can be calculated with any type of vehicle and through any inertial measuring device.

2.3 Measurement

IRI is evaluated by the road profile. It can be calculated in many ways: one of them is to use profilometers, classified as static or dynamic instruments by the World Bank, as we saw in section(1.1.1 at page 3). Static instruments are then divided into two classes (page: 5); the dynamic ones can be also grouped in another class: the Class 3 (in World Bank's terminology). The most common measurements are done with Class 1 instruments, capable of directly measuring the road profile. Class2 instruments are frequently used, and latest Class 3 instruments, which use correlation equations.

2.3.1 Motivation of Correlation Equations

RTRRMSs (Class 3): *Calibration by correlation equation is required for an RTRRMS for many reasons*, including these important three[14]:

1. The overall dynamic response of any particular RTRRMS vehicle will differ from the reference response. This effect can cause the "raw" measure from the RTRRMS to be higher or lower than corresponding IRI values, depending on whether the RTRRMS is more or less responsive than the reference.
2. The roadmeter in the RTRRMS generally has free play and other forms of hysteresis that cause it to miss counts, resulting in lower roughness measures.
3. The RTRRMS suspension motions include some effects factors other than road roughness. This induces higher roughness measures. The systematic error sources in an RTRRMS interact and are nonlinear. Their effect can change with roughness, surface type, temperature, and other environmental factors. The only way they can be taken into account is through correlation with measures of IRI obtained with a reference method (Class 1 or 2). This operation is essentially a "calibration by correlation."

Using World Bank terminology, these correspond to Information Quality Level (IQL) 1 and IQL-3 devices, representing the relative accuracy of the measurements[7]. IQL-1 systems measure the profile direction, independent of speed, and IQL-3 systems typically have correlation equations for different speeds to relate the actual measurements to IRI. IQL-1 systems typically report the roughness at 10 to 20 m intervals; IQL-3 at 100m+ intervals.

2.3.2 Information Quality Level

As described in Bennett and Paterson[6], imagine looking out of an aeroplane window. Is possible recognise the landscape by a line of a river or like a highway cuts through the landscape. The plane draws nearer, and you can recognise out your neighbourhood, then your home, your car. You have been looking at the same spot throughout the descent, but the "*information*" available to you become more accurate. While from high above you had enough macro-level information to determine what town you were looking at, you needed a different kind of micro-level information to determine precisely where your car was. Is just experienced first hand the principle behind Information Quality Levels (IQL), introduced by Paterson and others[16]. IQL helps to structure road management information into different levels that correlate to the degree of sophistication required for decision making and methods for collecting and processing data.

In IQL theory, very detailed data ('low-level data') can be aggregated into progressively simpler forms (higher-level data), as shown in Figure2.2. Five levels of road management have been identified for general use and are defined in Table??. IQL-1 represents fundamental, research, laboratory, theoretical, or electronic data types, where numerous attributes may be measured or identified. IQL-2 represents a level of detail typical of many engineering analyses. IQL-3 is a simpler level of detail, typically two or three attributes, which might be used for large production uses like a network-level survey or where simpler data collection methods are appropriate. IQL-4 is a summary or a key attribute which has use in planning, or in low-level data collection. IQL-5 represents top-level data such as key performance indicators, which typically might be combined key attributes from several elements of information. Furthermore higher levels can be defined as necessary. At IQL-1, pavement conditions are described by twenty or more attributes. At IQL-2, these would be reduced to 6-10 attributes, one, or two for each mode of distress. At IQL-3, the number of attributes is reduced to two to three, particularly, roughness, surface danger, and texture resistance. At IQL-4, all of the lower-level attributes may be condensed into one attribute, "Pavement Condition" (or "state" or "quality"), which may be measured by class values (good, fair, poor) or by an index (e.g., 0-10).

An IQL-5 indicator would combine pavement quality with other measures such as structural adequacy, safety aspects, and traffic congestion representing a higher order information, such as "road condition".

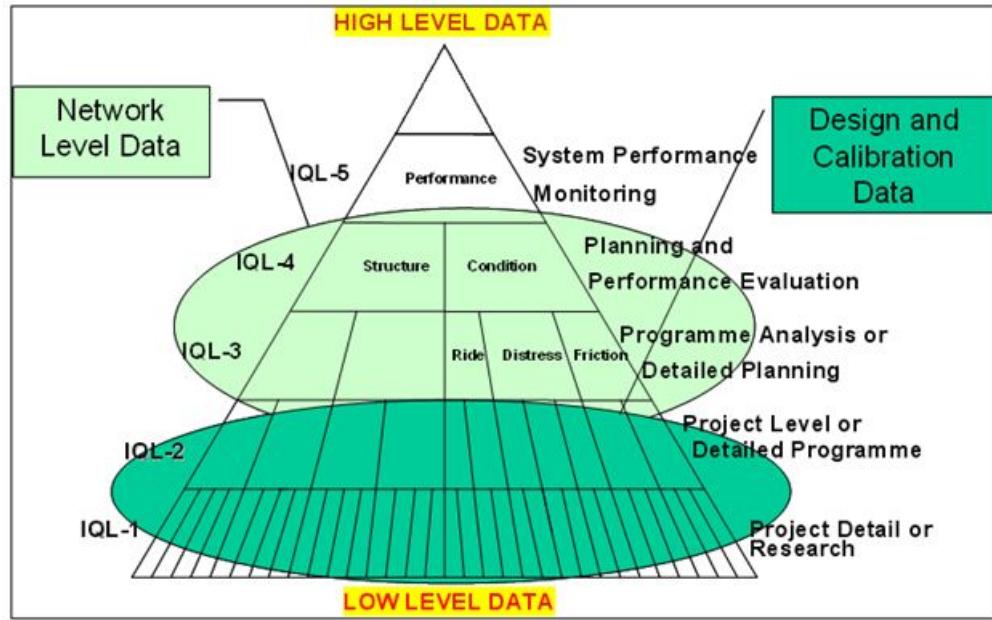


Figure 2.2: Information Quality Level Conception

From the previous definition of IQL is possible to identify three observation.

- The higher the decision-level, the higher the IQL. Information at IQL-4 or IQL-5 is appropriate for performance indicators and road statistics, because they are, easily understand without much technical background. At the project-level, however, the appropriate IQL depends much on the standard of the project and the resources of the agency. For example, IQL-3 is usually sufficient for a rural road or a small local agency. For most agencies and main roads, IQL-2 is typical, but for expressways, also IQL-1 may be used in some instances. The criteria to select the appropriate IQL depends if the decision is altered by having more detailed information, and so with a different IQL level.

- Primary data collection at a low-level (detailed) IQL typically costs more and involves more sophisticated instrument than the collection of higher IQL data. So, the IQL for primary data collection that is appropriate to a given agency and situation depends on the financial and physical resources, skills, cost, speed or productivity, the degree of automation, complexity, all to obtain a sustainable method, such as the regular operation of a road management system.
- A higher level IQL often represents an aggregation or transformation of the lower level IQLs. When there is a specific rule or formula for conversion, from IQL-2 into IQL-3, then the information is reproducible and reliable. Thus, when the appropriate IQL is chosen, the data can be re-used through a transformation to the higher IQLs and this avoids the need for repeating surveys and saves cost.

According to Bennett and Paterson[6] was defined the following table of the amount of detail of each IQL level.

IQL	Amount of Detail
1	The Most comprehensive level of detail, such as that which would be used as a reference benchmark for other measurement methods or in fundamental research. Would also be used in detailed field investigations for an in-depth diagnosis of problems, and for high-class project design. Normally used at project-level in special cases and unlikely to be used for network monitoring. Requires high-level skill and institutional resources to support and utilize collection methods.
2	A level of detail sufficient for comprehensive programming models and for standard design methods. For planning, would be used only in sample coverage. Sufficient to distinguish the performance and economic returns of different technical options with practical differences in dimensions or materials. Standard acquisition methods for project-level data collection. Would usually require automated acquisition methods for network surveys and use for network-level programming. Requires reliable institutional support and resources.
3	Sufficient detail for planning models and standard programming models for full network coverage. For project design, would suit elementary methods such as catalogue-type with meagre data needs and low-volume road/bridge design methods. Can be collected in network surveys by semi-automated methods or combined automated and manual methods.
4	The basic summary statistics of inventory, performance, and utilization that are of interest to providers and users. Suitable for the simplest planning and programming models, but for projects is suitable only for standardised designs of very low-volume roads. The simplest, most basic collection methods, either entirely manual or entirely semi-automated, provide direct but approximate measures and suit small or resource-poor agencies. Alternatively, the statistics may be computed from more detailed data.

Table 2.1: Classification of Information by Quality and Detail

2.3.3 Quarter Car Model

For the calculation of the IRI index, it is necessary to define a standard reference vehicle[14]. This vehicle, for reasons of simplifying the index calculation process, was identified in the quarter-car model shown in Fig. 2.3. This model is two-dimensional because the only movement in the Z direction is taken into consideration. This model schematizes the vehicle with a sprung mass and a unsprung mass, connected by a shock absorber and a suspension, identified by a spring with own elastic constant and connected to the road pavement through the tire, also simplified with a spring of an elastic constant[14].

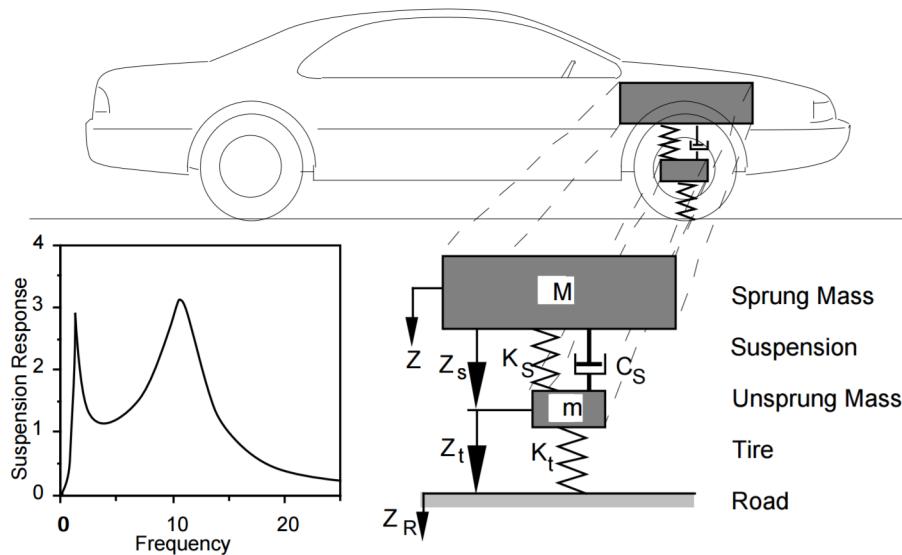


Figure 2.3: Quarter Car Model and Frequency Response

The roughness is seen as deviations in elevation[11] (displacement inputs), slope (velocity inputs), or change of slope (acceleration inputs), so the quarter car responds in a defined manner. The response can be mathematically described with a relatively simple set of dynamic equations known as a quarter-car simulation.

$$\begin{cases} \ddot{Z}_s m_s + C_s (\dot{Z}_s - \dot{Z}_u) + K_s (Z_s - Z_u) = 0 \\ \ddot{Z}_u m_u + C_s (\dot{Z}_u - \dot{Z}_s) + K_s (Z_u - Z_s) + K_t (Z_u - Z_p) = 0 \end{cases}$$

where the symbols represents:

Z_s = The quote of sprung mass relative to the static equilibrium position,

Z_u = The quote of unsprung mass relative to the static equilibrium position,

Z_p = Road pavement height at fixed point,

m_s = Sprung mass,

m_u = Unsprung mass,

k_s = Elastic subspension constant,

k_u = Elastic tire constant,

C_s = Damper damping constant.

the system of two second order differential equations can be simplified by normalizing the parameters mu , kt , ks , cs from the suspended mass m_s , according to the positions[11]:

$$\mu = \frac{m_u}{m_s}; \quad k_1 = \frac{k_t}{m_s}; \quad k_2 = \frac{k_s}{m_s}; \quad c = \frac{C_s}{m_s}$$

leaving the equations in this form:

$$\begin{cases} \ddot{Z}_s + C_s(\dot{Z}_s - \dot{Z}_u) + K_1(Z_s - Z_u) = 0 \\ \ddot{Z}_u\mu + C_s(\dot{Z}_u - \dot{Z}_s) + K_2(Z_u - Z_s) + K_1Z_u = K_1Z_p \end{cases}$$

thus, the system becomes a system of four differential equations of the first order that in matrix form can be expressed as:

$$\begin{bmatrix} \dot{Z}_s \\ \ddot{Z}_s \\ \dot{Z}_u \\ \ddot{Z}_u \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ -k_2 & -c & k_2 & c \\ 0 & 0 & 0 & 1 \\ \frac{k_2}{\mu} & \frac{c}{\mu} & -\frac{k_1 + k_2}{\mu} & -\frac{c}{\mu} \end{bmatrix} * \begin{bmatrix} Z_s \\ \dot{Z}_s \\ Z_u \\ \dot{Z}_u \end{bmatrix} + Z_p * \begin{bmatrix} 0 \\ 0 \\ 0 \\ \frac{k_1}{\mu} \end{bmatrix}$$

Where the resultant vector represents the vector of the state variables, i.e. the variables that are needed to fully define the state of the system. For the standard vehicle used in the IRI definition, the average values of American vehicles were obtained, this values obtained are called "**Golden Car**"[14].

It presents the following coefficient values for the quarter of a vehicle:

Parameter	Value
c	6.0 s^{-1}
K_1	653 s^{-2}
K_2	63.3 s^{-2}
μ	0.15

Table 2.2: Golden Car Parameter

About the frequency response of the model, at very low frequencies (corresponding to long wavelengths in the road) the suspension response is zero because the wheel and the vehicle body move up and down together. The response is maintained up through frequencies near 10 Hz where axle resonance occurs. Above the axle resonant frequency, the response again drops to zero as the road bumps simply deflect the tire without producing significant suspension stroke. The frequency response of the quarter car extends from approximately 0.5 to 20 Hz.

2.4 Calculation of IRI

Note the values, instant for instant, of the displacement velocities Z_s and Z_u obtained by integrating from the system of equations describing the motion of the Quarter car model, the calculation of the IRI is performed by the formula:

$$IRI = \frac{1}{L} \int_0^V |\dot{Z}_s - \dot{Z}_u| dt$$

where L is the profile length and V is the standard speed of 80 km h^{-1} . Generally IRI is measured in mm km^{-1} or in mile^{-1} . This index, as defined, is comparable to two profiles, meaning that if a 500 m profile has an IRI index of 100 mm km^{-1} and the next 500 m profile has an IRI index of 200 mm km^{-1} , The entire 1000m profile will have an IRI of 150 mm km^{-1} , and this is one of the most important features[14] of that index.

The measurement and calculation procedure of IRI are also based on the following principles:

- A single longitudinal profile with sample interval not longer than 300 mm is measured.
- The measured profile is smoothed with a 250mm base length moving average filter known as IRI filter.
- The slope between consecutive elevation points is considered to be constant.

The IRI index is calculated by filtering the measured profile with the quarter car filter, at a simulation speed of 80km h^{-1} , so that it provides a summary value of the slope, as it is recorded by the vehicle. The algorithm used for the IRI value calculation uses a theoretical filter describing the quarter car theoretical response to pavement surface irregularities.

As mentioned briefly earlier, the IRI index has been defined to classify road pavements in terms of driving comfort in the vehicle and damage to the pavement. Indeed, the correlation between IRI and comfort or damage is remarkable[11].

3

Inertial Measurement Unit

Inertial sensors, called Inertial Measurement Unit (**IMU**), is an electronic device of measurement that allows to estimate specific force, angular velocity and sometimes the magnetic field of a body from the inertial forces that the body experiences. Its operation principle is based on the use and a combination of forces from accelerometers, gyroscopes, and sometimes magnetometers.

The inertial technology is based on the first two Newton's laws.

The first law, affirms that the movement of a body is uniform and linear unless an external force is acting on it.

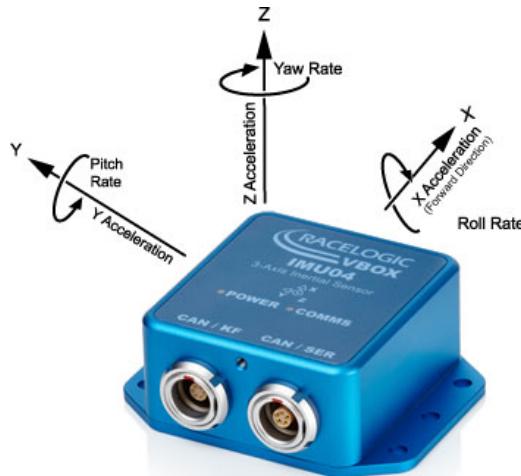
The second law defines that this force exerted on the mass will produce a proportional acceleration. $\mathbf{F} = m\mathbf{a}$

These relationships represent a *measurement principle* from which can be developed sensing devices able to measure the movement of bodies. If we know the magnitude and direction of the forces applied to a body and its mass, we can know its acceleration. Speed and position are obtained from the acceleration versus time, by first and second mathematical integration. Recent developments allow the production of IMU compatible

with GPS devices. An IMU allows a GPS receiver to operate when GPS signals are not available, e.g. in tunnels, buildings or in the presence of electronic interference[13].

3.1 Operational Principles

An IMU is a single unit into an electronics module which detects and collects angular velocity using one or more gyroscopes, linear acceleration data using one or more accelerometers and sometimes magnetic fields by using one or more magnetometer. A typical configuration of IMU contains two separate sensors. First is the three-axial accelerometer. It generates three signals describing the accelerations along each of its axes. Second is the three-axial gyroscopes, it outputs three analogue signals, and describe the vehicle angular velocity for each of the sensor axes. Another possible configuration contains also a three-axial magnetometer that produced three signal along each axis that describing the magnetic field around the body.



Racelogic Inertial Measurement Unit (RLVIMU04) provides highly accurate measurements of pitch, roll, and yaw rate using three rate gyros, as well as x , y , z acceleration via three accelerometers. The RLVIMU04, produced by VBOX Automative, is designed for use either as a standalone sensor with simple connection and configuration via the CAN bus interface, or for use with VBOX GPS data loggers. When used in conjunction with VBOX 3i, data from the IMU can be seamlessly integrated with GPS to produce *pitch* and *roll* angle accurate to 0.06° (RMS) as well as smoother velocity data. This ensures GPS data even when satellite reception is interrupted.

Figure 3.1: Example of Racelogic IMU Box

The three axes around the sensors that produce the signals are **pitch**, **roll**, and **yaw**, in fact, IMUs works by detecting the changes in pitch, roll, and yaw.

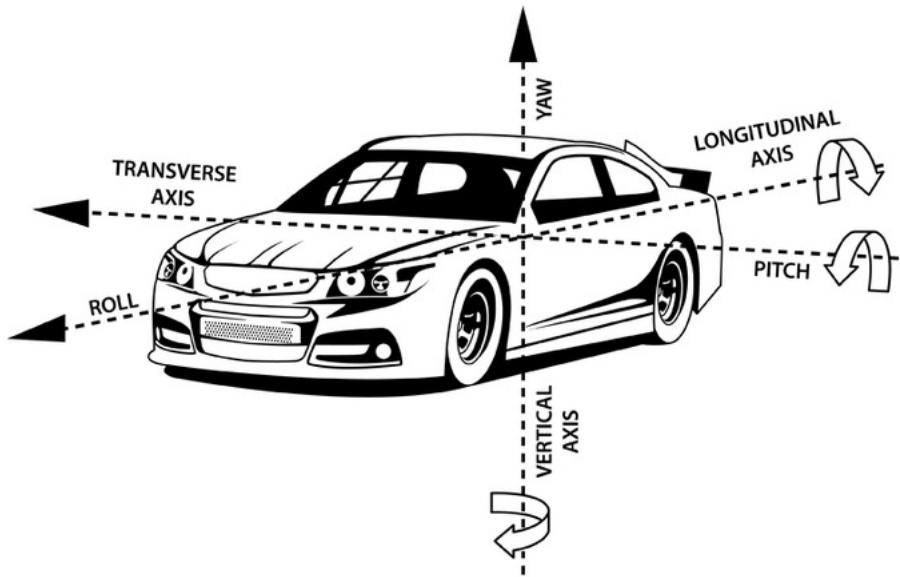


Figure 3.2: Frame of car respect Yaw, Pitch, and Roll Angle.

Pitch: The pitch axis (also called lateral axis) has its origin at the centre of gravity and is directed to the right

Roll: The roll axis (or longitudinal axis) has its origin at the centre of gravity and is directed forward

Yaw: The yaw axis (Vertical axis) has its origin at the centre of gravity and is directed towards the bottom of the vehicle

3.1.1 Applications

Nowadays, IMU are often incorporated into Inertial Navigation Systems (INS), which uses the raw IMU measurements, and after a processing and combination of these, is possible determine attitude, angular velocity, linear velocity and position relative to a global reference frame¹, in our case the frame of the vehicle, as is shown in the Figure???. The IMU are highly applied for the navigation and control of the military, civil, and many commercial vehicles for real-time monitoring, and for geodetic navigation through post-processing of data. Finding, ample space for use in space navigation systems, cars, ships, planes and aeroplanes.

The process to obtain velocity from acceleration and position from velocity, is known as dead reckoning². In land vehicles, an IMU can be integrated into GPS based automotive navigation systems³ or vehicle tracking systems⁴, giving at the system a dead reckoning capability and the ability to gather as much accurate data as possible about the vehicle's current speed, turn rate, inclination and acceleration. Besides navigational purposes, IMU serves as orientation sensors in many consumer products. Smartphones and Tablets contain IMU as orientation sensors. Fitness trackers and other wearable devices may also include IMU to measure motion. They are a competing technology for use in motion capture technology[26].

¹A reference frame consists of an abstract coordinate system and the set of physical reference points that uniquely fix the coordinate system and standardize measurements.

²The idea is to start from a known state (e.g. holding still) and calculate a new state (e.g. moving up or down) based on a measurement that indicates change, although it does not actually give you the info you want directly.

³An automotive navigation system is part of the automobile controls or a third party add-on used to find direction in an automobile. It typically uses a satellite navigation device to get its position data which is then correlated to a position on a road

⁴A vehicle tracking system combines the use of automatic vehicle location in individual vehicles with software that collects these data for a comprehensive picture of vehicle locations

3.2 Inertial Navigation System

An inertial navigation system (INS) is able to process the reported IMU data by a processor, like motion sensors (accelerometers) and rotation sensors (gyroscopes) to continuously calculate via dead reckoning the position, orientation, and velocity of a moving object without the need for external references[3]. The guidance system could show at pilot where the vehicle is located geographically at a certain moment, as with a GPS navigation system, but without the need to communicate with or receive communication from any outside components, such satellites. External sources are however used in order to correct drift errors.

Recent advances in the construction of microelectromechanical systems (MEMS)⁵ have made the possibility to manufacture small and light inertial navigation systems, they are widely used in mobile devices, thanks to their small size without compromising performance.

3.2.1 Principal Sensors

The main sensors of IMU system as we have discusses in the introduction3.1 are the Accelerometer and Gyroscopes:

Accelerometer: measure the linear acceleration of the moving vehicle in the sensor or body frame, but in directions that can only be measured relative to the moving system (the accelerometers are fixed to the system and rotate with the system, but are not aware of their own orientation). This can be thought as the ability of a blindfolded passenger in a car to feel themselves pressed back into their seat as the vehicle accelerates forward or pulled forward as it slows down, and feel pressed down into their seat as the vehicle accelerates up a hill or rise up out of their seat as the car passes over the crest of a hill and begins to descend. Based on this information alone, they know how the vehicle is accelerating relative to itself, that is, whether it is accelerating forward, backwards, left, right, up (toward the car's ceiling), or down (toward the car's floor) measured relative to the car, but not the direction relative to the Earth, since they did not know what direction the car was facing relative to the Earth when they felt the accelerations. Note that the accelerometers will actually detect a force that is directed in the opposite

⁵MEMS is the technology of microscopic devices, particularly those with moving parts.

direction from the acceleration vector.

Gyrosopes: measure the angular velocity of the sensor frame with respect to the inertial reference frame. By using the original orientation of the system in the inertial reference frame as the initial condition and integrating the angular velocity, the system's current orientation is known at all times. This can be thought of as the ability of a blindfolded passenger in a car to feel the car turn left and right or tilt up and down as the car ascends or descends hills. Based on this information alone, the passenger knows what direction the car is facing but not how fast or slow it is moving, or whether it is sliding obliquely.

An INS system is useful for a real-time monitoring but is possible getting the information about the velocity and position after processing IMU data when the travel is finished and the data are sent to a server or are stored into a device.

3.3 Smartphone Sensors

Nowadays, smartphones are widely used in the world, and they are equipped with many sensors such as an accelerometer, gyroscope, touch-screen, ambient light sensor, proximity sensor, magnetometer, barometer, heart pulse rate monitor, for the purpose of this work the main sensor used is the accelerometer. Smartphone sensors are very cheap, and their size is getting smaller and smaller, in fact, they are also called Micro-Electro Mechanical-Systems (MEMS), motion sensors, and can offer great data results if compared with more both expensive and professional, so the information given by IMU is useful if the relations between the smartphone reference system, the vehicle reference system and the world reference system are known, in fact, by getting this information in real-time from the motion sensor is possible to create an inertial navigation system by sensor data or process after the travel is finished if the data are stored, in fact, there are many applications to allow the registration of the smartphone sensors data, it also be useful combine the use of the GPS.

These sensors are capable of providing raw data with high precision and accuracy and are useful to monitoring three-dimensional device movement or positioning, or changes in the ambient environment near a device. Usually, a smartphone platform supports three broad categories of sensors[4]:

- **Motion sensors:** they measure acceleration forces and rotational forces along three axes. This category includes accelerometers, gravity sensors, gyroscopes, and rotational vector sensors.
 - **Environmental sensors:** they measure various environmental parameters, such as ambient air temperature and pressure, illumination, and humidity. This category includes barometers, photometers, and thermometers.
 - **Position sensors:** They measure the physical position of a device. This category includes orientation sensors and magnetometers.

Simplified view of a smart-phone board

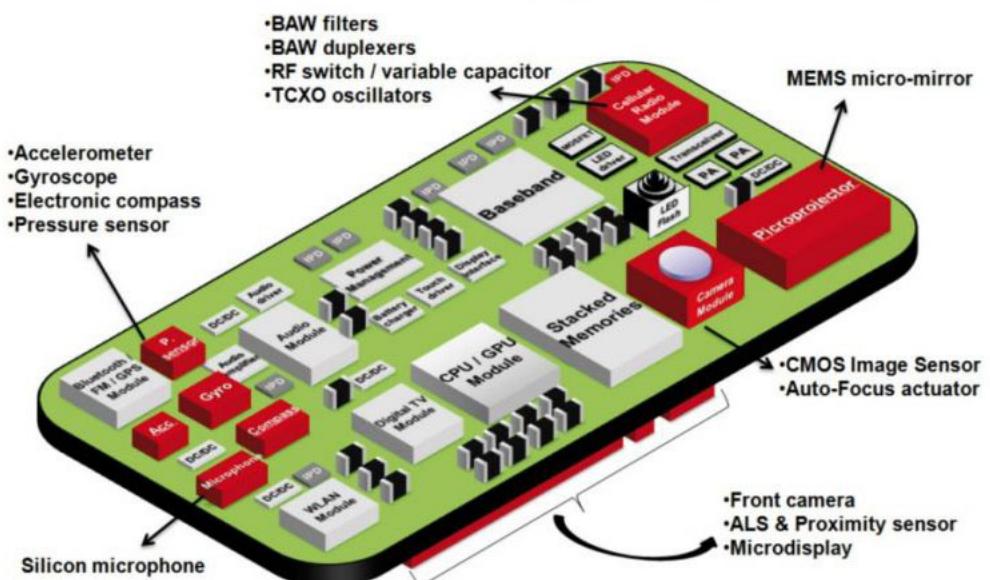


Figure 3.3: Sample view of the principals sensors inside smartphone

Accelerometer

Smartphones are built with an accelerometer sensor. They are sensitive to both linear acceleration and the local gravitational field, for each of the three-axes. The accelerometer measures the acceleration of a smartphone against free fall, so allowing an application both determine the movement of the smartphone and its inclination. The sensor consists of two components, a fixed and a mobile. The second, moving according to the vibrations received, allows the first to measure and process the received data, then the distance variation between the capacitor⁶ armatures (so the electric capacity variation) will be used to determine the variation of the forces of acceleration which is subjected a device. A special circuit records the variations created within the capacitor (these capacitors armatures are, made up of a moving mass and the fixed structure of the device) so that it can generate an electrical signal, proportional to the displacement of a mass. The measurement is done for each axis (x , y , and z .), and it will be possible to measure the three-dimensional acceleration variation. The figure below^{3.5} show the internal structure of accelerometer sensor.

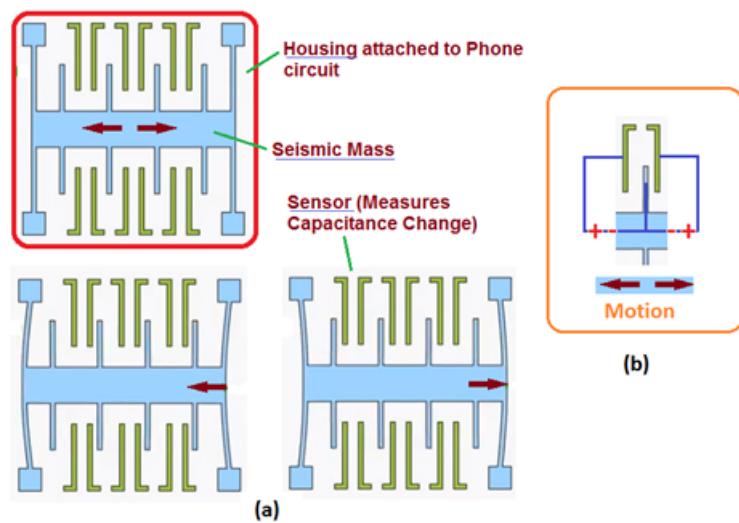


Figure 3.4: Internal structure of smartphone accelerometer sensor

⁶A capacitor is a passive two-terminal electrical component that stores electrical energy in an electric field.

Gyroscopes

The gyroscopes detect the current orientation of the device or changes in the orientation. Orientation can be computed from the angular velocity detected by the gyroscope, expressed in *rad/s* on the three-axis. A triple axis MEMS gyroscope can measure rotation around the three axes: *x*, *y*, and *z*. When the gyro is rotated, a small resonating mass is shifted as the angular velocity changes. This movement is converted into very low-current electrical signals that can be amplified and read by a host microcontroller. The figure below shows the internal structure of gyroscopes inside the smartphone.

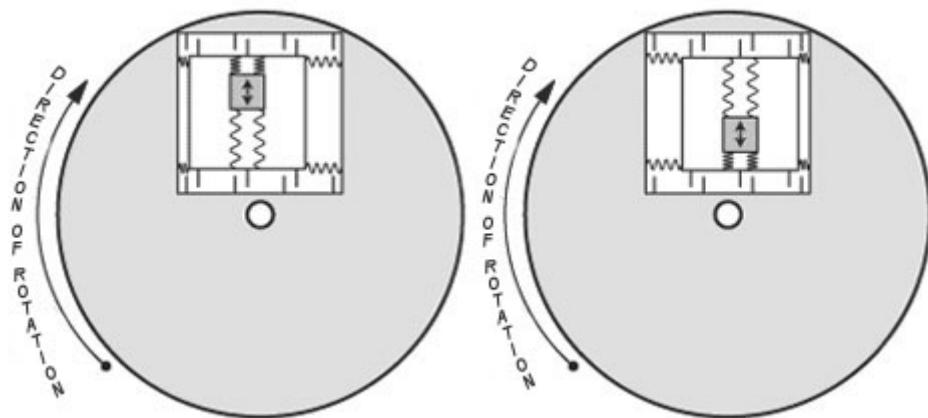


Figure 3.5: Internal structure of smartphone gyroscopes sensor

GPS

All smartphones have GPS (Global Positioning System acronym), it is able to give our position. In good condition, a GPS receiver indicates the location with an accuracy of about 10 m. The aim of GPS system is to provide the coordinates of our position in terms of latitude, longitude and altitude. The GPS system technically consists of 3 levels called segments:

Spatial Segment is given by 31 satellites rotating around the earth and which are the heart of GPS operation. The satellites travel to over 20.000 km from the ground.

Control Segment is provided by the main control station (and one of the reserve). The US military aircraft control satellites and carries out all related maintenance operations.

User Segment is simply the device with integrated GPS: navigator, smartphone, tablet, etc..

GPS can find our position on earth knowing:

- The distance from at least 3 satellites
- The position of the satellites

The GPS receives the radio signal from the satellite that orbits in its vicinity and thanks to this signal can calculate its distance using the simple formula:

$$Distance = Time * Speed$$

Speed: Satellite signal travels at speed of light ($299,792 \text{ km s}^{-1}$) Time: To find the time value, the satellite and the GPS of device (receiver) start from a common base signal, when the receiver has to calculate the position, receives from the satellite the signal, but having to travel thousands of kilometers the signal will come with a certain delay, this delay is the travel time we're looking for. The signal usually arrived about in the order of 100ths of a second. By multiplying the speed and travel time, our receiver will have distances from the satellites. To this end, the satellite sends the track of its position over time (which is stored in our device). Once we have the exact distances from the satellite and its position, it is possible to find our position on the earth. Triangulation technique is used for the purpose, through the information from the 3

satellites we solve a system of 3 equations with 3 unknowns: Latitude, Longitude and Altitude.

In general, the triangulation technique allows finding exactly our position as the intersection of three spheres having a radius equal to the distance of our point from the point of reference. Actually, the intersection of the spheres produces two points in the space (one up and one down), but the problem is solved because considering the Earth sphere and inserting it into the geometric calculation we will have a single point on the earth surface representing our current position. As shown in the figure 3.6 below.

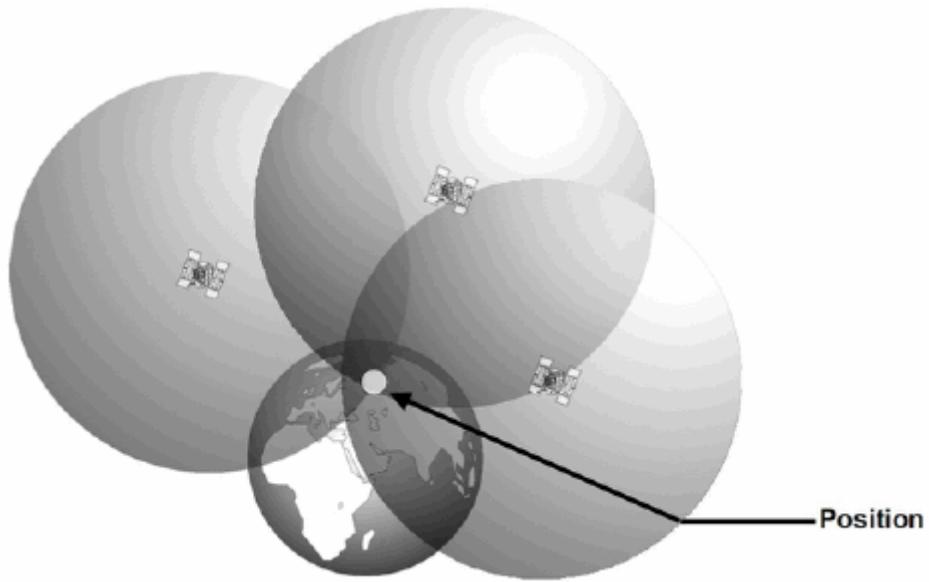


Figure 3.6: Triangulation technique

There are 3 types of modes available on smartphones to get the GPS signal:

- **High Accuracy:** uses data networks, Bluetooth, Wi-Fi or GPS to get the location
- **Battery Saver:** uses data networks, Bluetooth or Wi-Fi to get the location
- **Only Device:** only uses the GPS sensor signal.

GPS works at 1 Hz once connection is established, thus the application records a sample of data once per second on average

Other Sensors

However, there are still many sensors available on smartphones, and they are:

Magnetometer: detect magnetic fields. (compass applications use this to point at the planet's north pole)

Proximity sensor: it is placed near the earpiece of a phone. During a call, this sensor lets the system know that you're most probably in a call and that the screen has to be turned off.

Light sensor: measures how bright the ambient light is. The phone's software uses this data to adjust the display's brightness automatically.

Barometer: measures atmospheric pressure. Data measured by it is used to determine how high the device is above sea level, which in turn results in improved GPS accuracy.

Thermometer: measures ambient temperature. Some handsets might have more than one of them(to monitor the temperature inside the device and its battery)

Pedometer: is a sensor used for counting the number of steps that the user has taken.

Heart rate monitor: measure one's pulse, and it does that by detecting the minute pulsations of the blood vessels inside one's finger.

Fingerprint sensors: the sensor is most convenient to use, as it does not require swiping in order to read fingerprint data.

3.4 Accuracy

The major disadvantage of using IMU for navigation is that they typically suffer from accumulated error. Because the guidance system is continually integrating acceleration respect to the time to calculate velocity and position, any measurement errors, however small they are, are accumulated over time. This leads to "*drift*": an ever-increasing difference between where the system thinks it is located and the actual location. For the integration, a constant error in acceleration results in a linear error in velocity and a quadratic error growth in position.[23] Signals from the IMU are processed by signal processing at a very high rate. For example, in a $100Hz$ IMU, the sample period represents the total motion of the IMU over 10 millis. To reduce the effect of the measurement errors, they must be understood, estimated and then corrected. A well-designed system filter estimates and removes errors from the IMU measurements, reaching a higher attitude accuracy and longer solution stability .

The general error terms.

Repeatability: the ability of the sensor to produce the same output for the same repeated input, assuming all other conditions are the same.

Stability: the ability of the sensor to produce the same output, over time, for the same constant input.

Drift: the change of the output over time (zero drift is the change over time with no input).

Even when an IMU is stationary, it still measures forces. These measurements are the result of the IMU measuring forces in an inertial frame, a reference, fixed in space and time. Gravity acts in the inertial frame. The strong effect of gravity acceleration can be measured by the accelerometers and is always significant when operating near the Earth's surface. Not all of these errors are relevant for all IMUs. Some of the error terms are too small to create a significant difference in the final solution. A key to having a high-performance processing system is to understand what the errors are in the system and developing ways to reduce or remove the errors and error sources, so a proper filter system needs to be developed, however, during the integration, the principal error is caused by the noise of the input IMU signal.

4

Data Analysis

As discussed in Chapter3 in the Error section(3.4 on page 34). IMU, during measurement, suffer from accumulated error. The measurement along the pathway of road surface consists of a sampling of measurements at specific time intervals (usually in the order of milliseconds). So the road profile can be seen as an electronically acquired digital signal and consequently, it is necessary to filtering the signal from the noise¹, it may also be useful to delete certain information in the signal that is not of interest, or correct it from the drift(3.4).

This procedure, called filtering, it is used in the theory of signal analysis. It is an essential aspect in the evaluation of the profile[14]. In brief, a digital filter represents a procedure that transforms a series of numbers into a new series of numbers[14]. From the measurement obtained by the sensors, particular attention is given to the vertical acceleration signal and to the rotation vectors.

¹An unknown modifications that a signal may suffer during capture

The rotation vectors will be useful for reorienting the signals obtained from the smartphone[4] respect to the vehicle axes, while the vertical acceleration signal will be subject to various filtering operations depending on the final index to be obtained.

First of all, it is necessary to pay some attention to some dynamics² physical principles, about the operations that can be done, on the acceleration signal to get the position and vice-versa.

Given a position versus time of an object, $x(t)$, the velocity, $v(t)$, can be found by taking the first derivative.

$$v(t) = \frac{dx}{dt} \quad (4.1)$$

Acceleration, $a(t)$, can be found by taking the second derivative of position or first derivative of velocity.

$$a(t) = \frac{d^2x}{dt^2} = \frac{dv}{dt} \quad (4.2)$$

However, is interesting to reverse this process and find the position signal given an acceleration signal. To do that, a double integration must be performed on the acceleration signal. In principle, using double integration on an acceleration signal to get a position signal, the initial position and initial velocity must be known. After the first integration, the initial velocity should be added to the result, as the initial position should be added after the second integration. These operations are illustrated in the following equations

$$v(t) = v(t_0) + \int_{t_0}^t a(\tau) d\tau \quad (4.3)$$

where:

Symbol	Description
t_0	Initial Time
$v(t_0)$	Initial Velocity

²Branch of mechanics that deals with the study of the motion of bodies and their causes or, more concretely, of the circumstances that determine and modify it

To get the position signal from velocity is used the followed formula:

$$x(t) = x(t_0) + \int_{t_0}^t v(\tau) d\tau. \quad (4.4)$$

where:

Symbol	Description
t_0	Initial Time
$x(t_0)$	Initial Position

Therefore, for a double integration of the acceleration, the two initial conditions (velocity and position) must be known to avoid integration errors. However, the only way to get these initial conditions is through direct measurement, which is often impractical or unobtainable. By data filtering, it is developed an approach that does not require knowledge of initial conditions. To perform a numerical integration it is necessary to choose one integration algorithm of the many existing. The acceleration signal is sampled, making it a discrete function of time having a sampling frequency, f_s , associated with it. The easiest way to perform numerical integration is to use the rectangular integration method. This method uses an accumulator to sum all past sampled inputs and the current input sample and divide by the sampling rate. Rectangular integration is represented by the following difference equation:

$$y(n) = \frac{1}{f_s} \sum_{k=0}^n x(n-k) = y(n-1) + \frac{1}{f_s} x(n) \quad (4.5)$$

Another numerical integration method uses the trapezoidal rule. The results are more precise with this method than the rectangular method. The difference equation for trapezoidal integration is:

$$y(n) = y(n-1) + \frac{1}{2f_s} [x(n-1) + x(n)], n > 0 \quad (4.6)$$

The figure below show the difference using both methods.

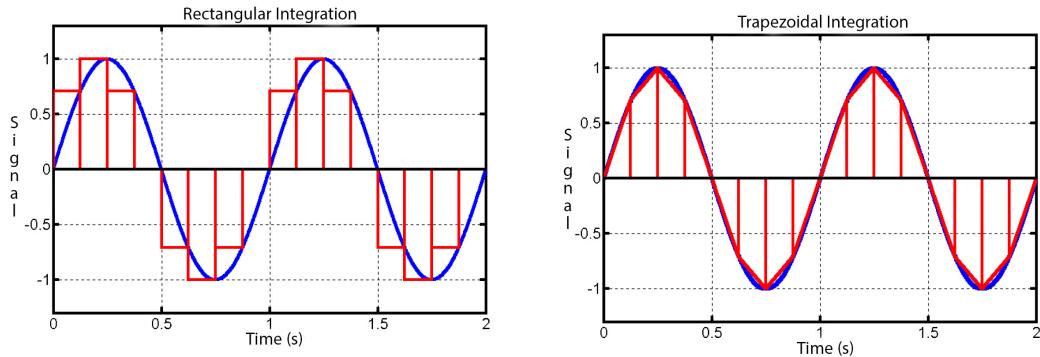
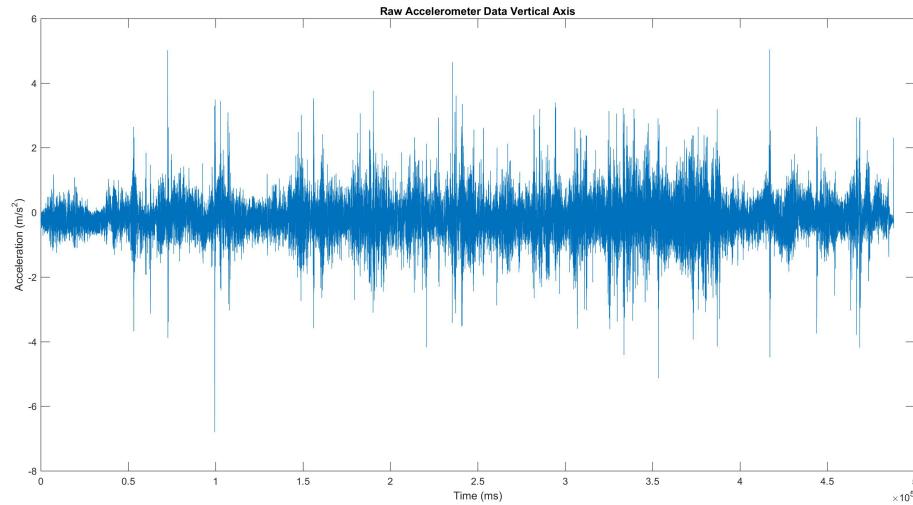


Figure 4.1: Integration using Rectangular (left) and Trapezoidal (right) methods of Sine Wave.

The integration was carried out using the trapezoidal method by the MATLAB suite. But without adequate filtering of the signal, the result presents a very error, caused by the drift and noise.

Various signal filtering procedures will be discussed.

The figure below shows the result of a raw signal integration using the trapezoidal method.



(a) Acceleration

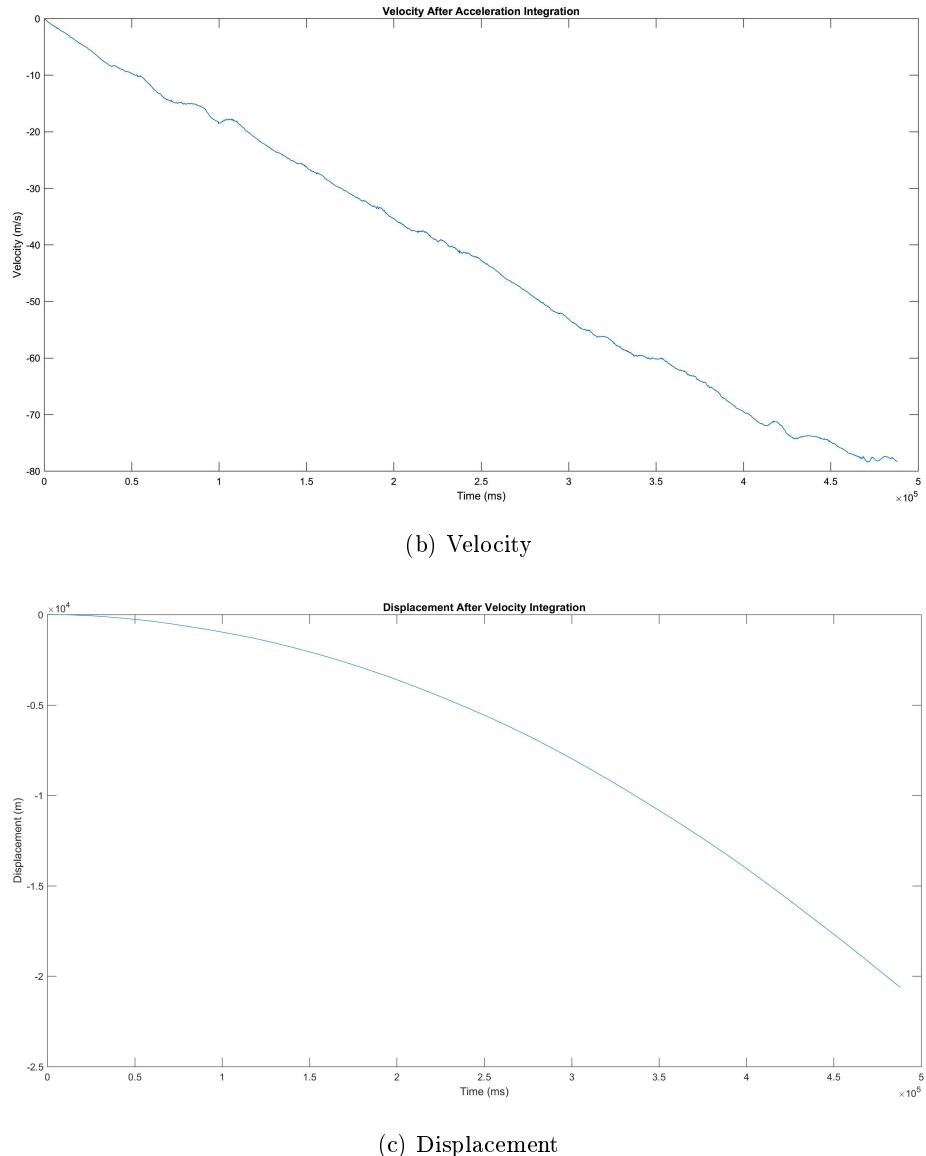


Figure 4.2: The result of double integration of a Raw Signal

As is possible see, the result is not realistic, considering it is vertical acceleration, so it is necessary to perform various steps to filter the signal. First of all, the signal reorientation will be carried out respect the axes of the vehicle, and subsequently, various filter operations to smooth the signal.

4.1 Accelerometer Reorientation

The Cartesian reference system of the phone must be aligned with the vehicle reference system, to detect the vehicle motion correctly. As shown in the figure below.

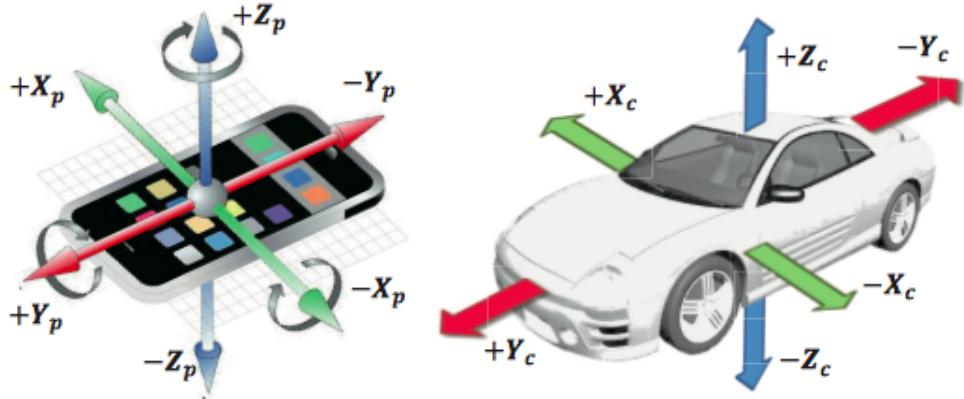


Figure 4.3: Correct alignment of smartphone respect to the vehicle cartesian frame.

Smartphone accelerometer detects the following accelerations: a_{x_p} , a_{y_p} and a_{z_p} . To determine the accelerations felt by the vehicle and locate road surface anomalies. The accelerometer must detect what happens in the direction perpendicular (Z axes) to the vehicle[15]. Respectively the X_p axis identifies the longitudinal direction, Y_p axis the transverse direction and Z_p the perpendicular direction respect to the xy plane.

To detect road anomalies, the direction of the z-axis must correspond to the direction of the z-axes. If this condition subsists, the accelerometer is well oriented, contrarily it is not well oriented and needs to be reoriented. But even if starting from a precise orientation condition, during travel the phone may be moving, or due to unexpected vehicle movements, travel of climbing, downhill, curve, all of these causes could affect the misalignment of the smartphone frame respect to the vehicle frame.

The reorientation can be performed by the Euler Angles. Three angles that allow to defining the orientation in space of any body through a succession of elementary rotations[8]. The XYZ sequence was defined, a rotation around the x -axis by an angle α (roll angle), one around the y -axis by β (pitch angle) and one around the z -axis by γ (yaw angle). The equations that allows to reoriented data by the α , β , γ , angle are:[4]

$$a_{x_{reor}} = \cos(\beta)a_{x_p} + \sin(\beta)\sin(\alpha)a_{y_p} + \cos(\alpha)\sin(\beta)a_{z_p} \quad (4.7)$$

$$a_{y_{reor}} = \cos(\alpha)a_{y_p} - \sin(\alpha)a_{z_p} \quad (4.8)$$

$$a_{z_{reor}} = -\sin(\beta)a_{x_p} + \cos(\beta)\sin(\alpha)a_{y_p} + \cos(\beta)\cos(\alpha)a_{z_p} \quad (4.9)$$

The figure below, show an example of reoriented data.

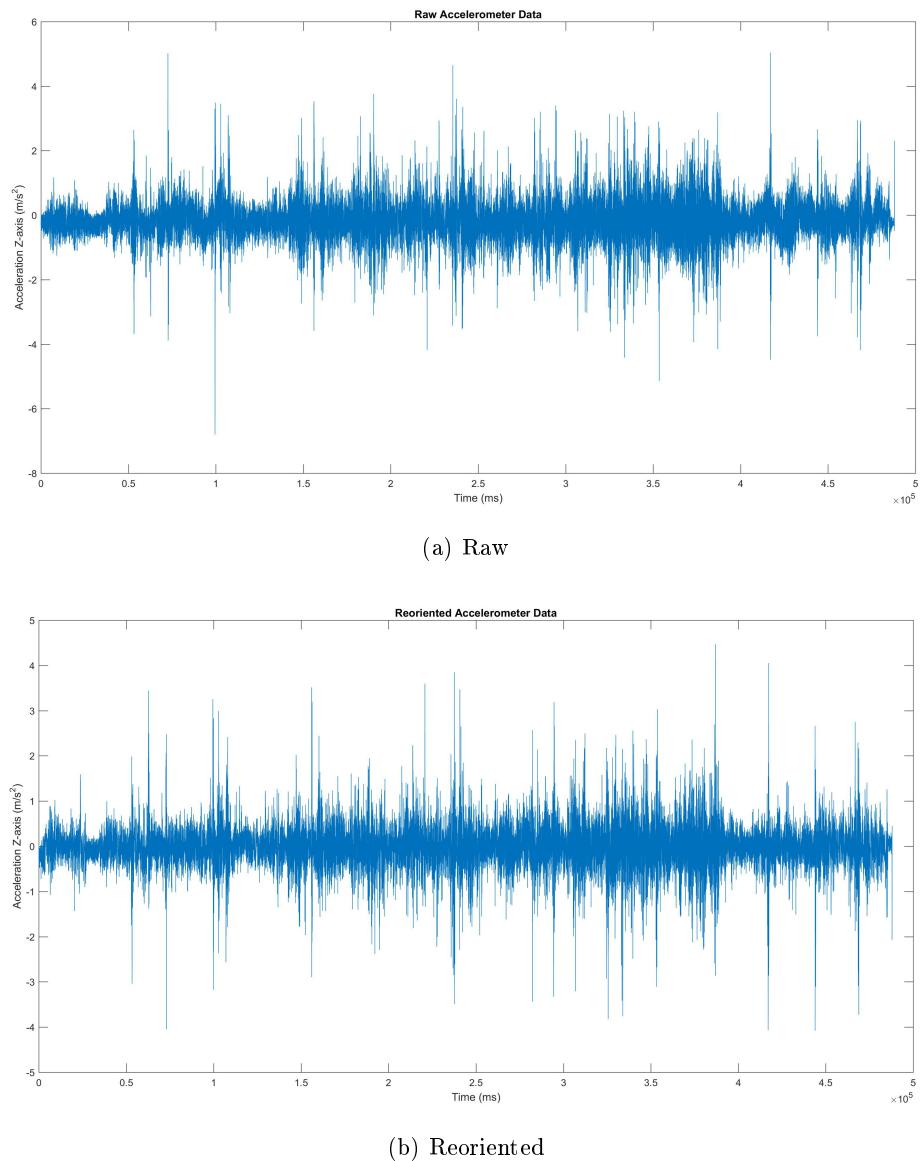


Figure 4.4: The result of reorientation of raw data

4.2 Data Filtering

As can be seen in figure 4.2, a data filtering operation is needed to smooth the signal and perform a better integration. It is necessary to apply:

- A series of preliminary filters for removing unimportant information.
- A digital filter for removing certain frequency components that cause the error at the stage of integration.

4.2.1 Preliminary Filtering

During signal capture, it is important to consider some information that can be removed, since they are not relevant to the final calculation. These principal regard:

- The background noise generated by engine vibrations.
- Acceleration components recorded at the moment the vehicle is stationary, so when its velocity is equal to 0 km h^{-1} .

These two filters are applied to all three indexes (IRI, Critical Points, Simple Acceleration Points) that are extrapolated from the data series.

Filtering Engine Vibrations

Considering the vehicle in a stationary position, both flat, uphill and downhill, with no any external form of acceleration given by the pilot, so at no speed. Many measurements have been made to see how much the engine vibration affects the process of data acquisition. Analyzing these measurements, two thresholds, one minimum and one maximum were identified, called respectively $a_{min_{th}}$ and $a_{max_{th}}$. Next, considering the generic acceleration signal at time a_t , the data series is thus modified:

$$\begin{cases} a_t = a_t - a_{max_{th}}; & \text{if } a_t > a_{max_{th}} \\ a_t = a_t + |a_{min_{th}}|; & \text{if } a_t < a_{min_{th}} \end{cases}$$

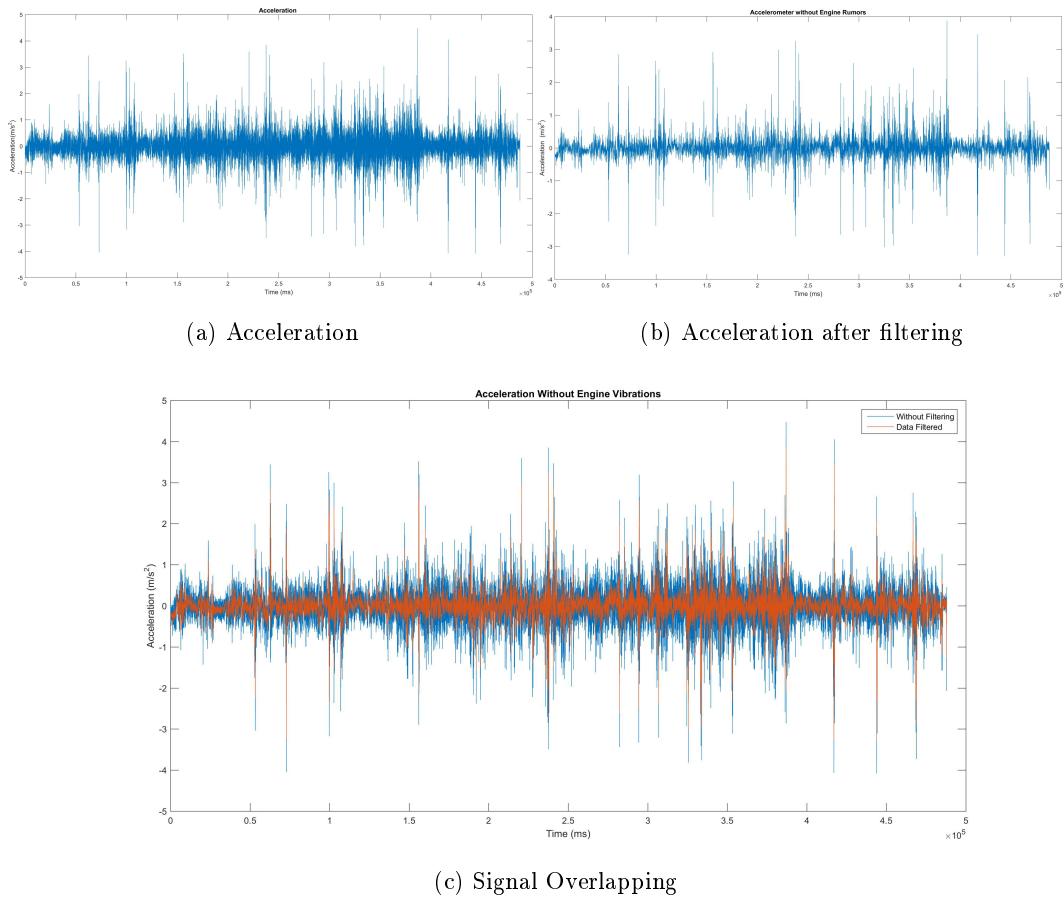
or:

$$a_t = \sqrt{\frac{1}{k}(a_{t_i}^2 + a_{t_{i+1}}^2 + \dots + a_{t_{i+k}}^2)}$$

$$if \quad a_{min_th} <= a_t <= a_{max_th}$$

Where k is the number of a predefined window, and all the values that fall into the window indexes will be considered. So the final value a_t will be calculated as the Root Mean Square of that values.

The figure below shows an example of applying the filter to a series of data subject only to the reorientation operation 4.1.



The original signal (a) is represented in blue, the filtered signal is represented in orange (b).

Figure 4.5: Application of Filtering Engine Vibrations

As is possible to see the signal when filtered it is much lighter, the background noise component produced by the engine is very resonant during the acquisition process and with this process it is possible to delete it.

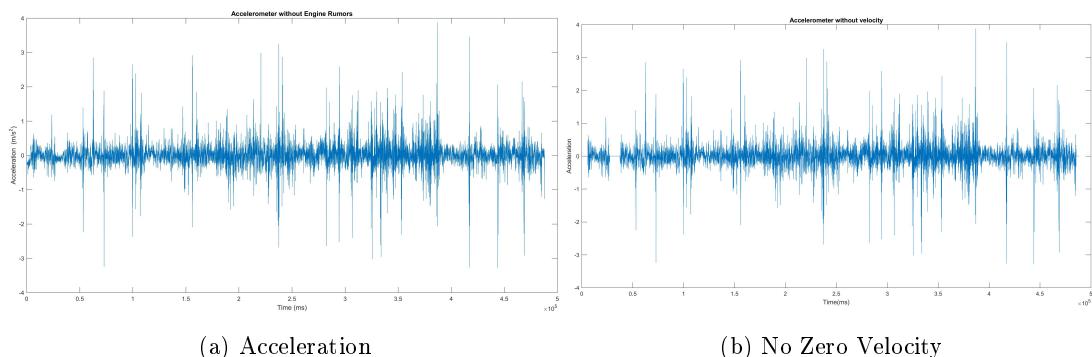
Zero Velocity Filter

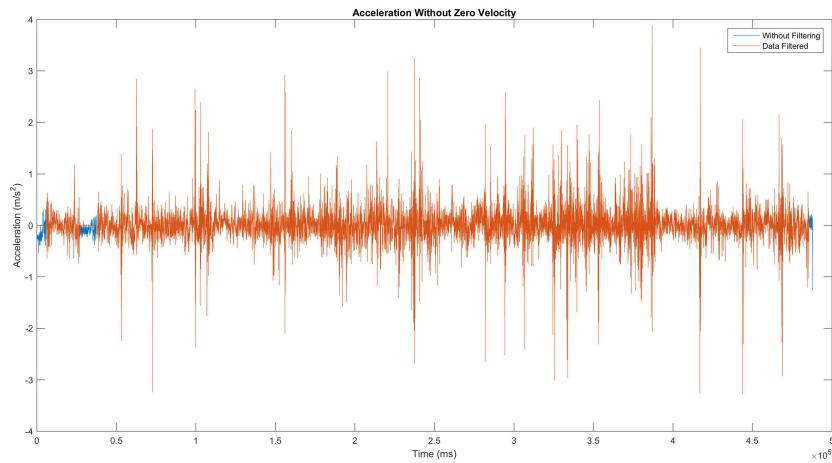
This filter brings attention to the cancellation of certain acceleration values that are associated with zero speed values. Due to several factors, it may happen that while the vehicle is stationary, because the registration starts even before the vehicle is in motion, or we are in intense traffic situations, stopped at a traffic light, and all other situations that may occur, making us stopped while the smartphone continues to read the data. If any of these conditions occur, the acceleration values can be cancelled, because they would not help us to understand the condition of the road surface.

It is possible to understand that speed a_t a given time (t) is equal to 0 km h^{-1} , thanks to GPS, because during smartphone recordings, gives us the speed of travel. Considering both signals at generic time (t), acceleration (a_t), and velocity (v_t), the data series is so modified:

$$\begin{cases} a_t = 0; & \text{if } v_t = 0 \text{ km h}^{-1} \\ a_t = a_t; & \text{if } v_t \neq 0 \text{ km h}^{-1} \end{cases}$$

The figure below shows an example of applying this filter to a series of data subject before to Filtering Engine Vibrations4.2.1.





(c) Overlapping

The original signal (a) is represent in blue, the filtered signal is represent in orange (b).

Figure 4.6: Application of Zero Velocity Filter

4.2.2 Digital Filtering

For IRI calculation, vertical displacement is needed, so the accelerometer data must be subject to a double integration process. Unfortunately, accelerometers have an undesired phenomenon named drift associated with them produced by a small DC component³ in the acceleration signal. Ideally, there should be no DC from the accelerometer for the measurement of a vibration. The presence of drift can direct to high integration errors. If the acceleration signal was integrated without any proper filtering, the output could become unlimited over time. The figure 4.2 shows what usually occurs to an acceleration signal after a double integration. Figure 4.2, is an example of acceleration signal that has a negative DC. To resolve the drift problem, a filter can be used to remove the DC component from the acceleration signal. Through filtering before integration, drift errors can be eliminated. For the initial conditions as discusses in 4, a solution is to use filtering. After the acceleration signal is integrated, it will possibly have a DC component. Again a filter can be used to remove that DC component of the signal. Furthermore, after the velocity signal is integrated to get the position, the position signal can be filtered as well. Filtering is a particular frequency process that attenuates certain bands of frequencies while passing others. These filters will pass the high-frequency content of a signal while rejecting the low. The specifications of a filter

³DC offset is a zero offset compensation. Refers to an electrical signal in which the value is shifted to a certain amount respect to the reference mass.

are its cutoff frequency, passband attenuation, and stop-band attenuation.

It is convenient if the filters are identical to each other to simplify the design.

There are two types of filters in the digital area: Infinite Impulse Response (IIR) filters and Finite Impulse Response (FIR) filters.

Finite Impulse Response

Finite Impulse Response, (FIR), is a type of digital filter characterised by a finite response, that, it is cancelled at a finite time. A FIR filter is described by the following difference equation:

$$y[n] = b_o x[n] + b_1 x[n - 1] + \dots + b_N x[n - N] = \sum_{i=0}^N b_i x[n - i]$$

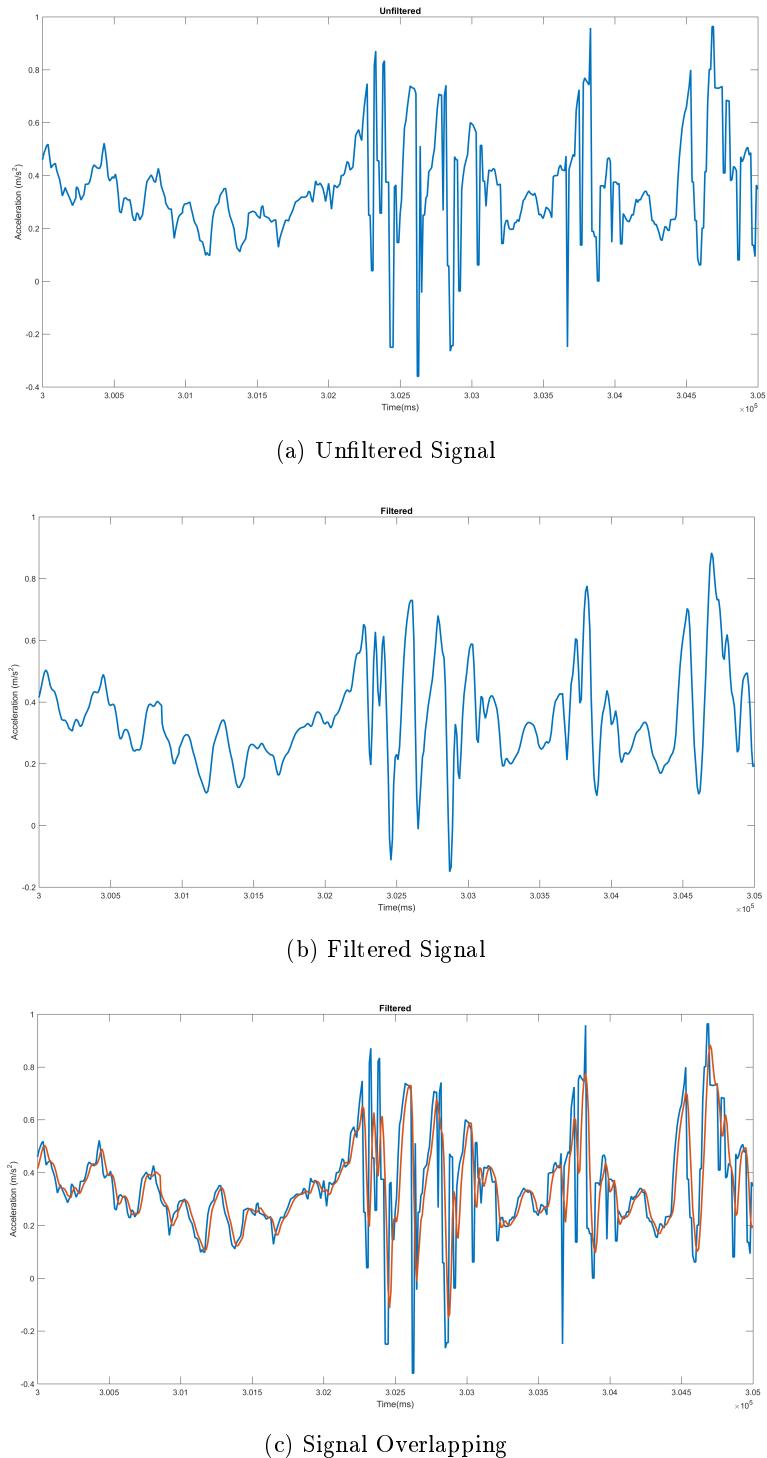
Where: $x[n]$ is the input signal, $y[n]$ is the output signal, N is the filter order, and b_i is the value of the impulse response at instant i . This filter is useful for the double integration process. It is recommended to use it because its phase response is linear, which is desired because different frequencies passing through the filter will have the same time delay. A disadvantage is that the order can be very high, and lead to excessive computations. For application to a vehicle road test, there is an interest in processing low-frequency signals. So the filter must have a low cutoff frequency with a clear transition band, making the order of the filter high.

Moving Average

An example of FIR filter is the moving average, commonly used in road pavement profiles, that defines the point A_i as the average of the points close to that one, for a base window of length n [14], defined like follow:

$$A_i = \frac{1}{n} \sum_{k=i}^{k=i+n} A_k$$

An example of application of the moving average filter is shown in the figure below:



The original signal (a) is represent in blue, the filtered signal is represent in orange (b).

Figure 4.7: Application of Moving Average Filter

Infinite Impulse Response

In signals theory, Infinite Impulse Response (IIR) is a dynamic system whose impulsive response is not anything for an infinite amount of time. IIR filtering is an alternative approach, that uses a recursive difference equation to represent the filter.

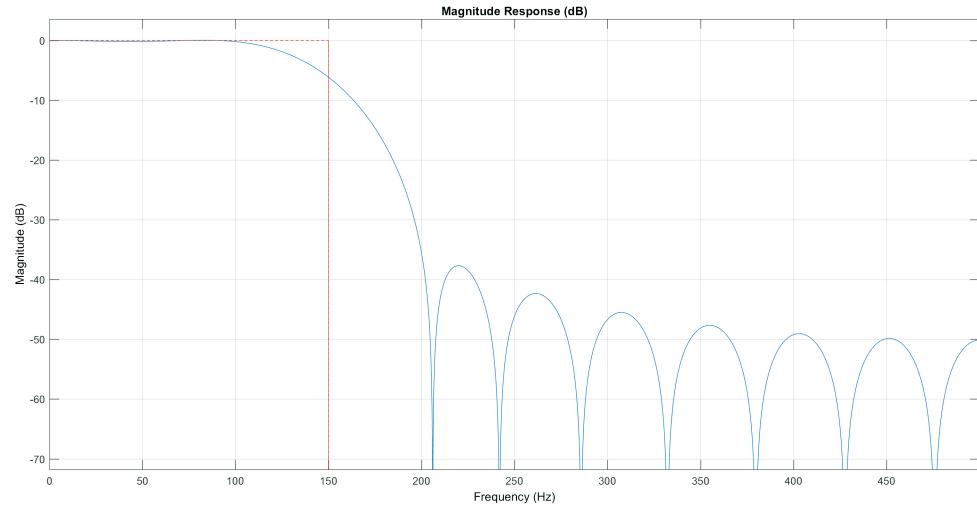
$$y[n] = a_0 \left(\sum_{i=0}^P b_i x[n - 1] + \sum_{j=1}^Q a_j y[n - j] \right)$$

Where $y[n]$ is the output and $x[n]$ is the input, the output is written as a combination of present and past inputs and past outputs.

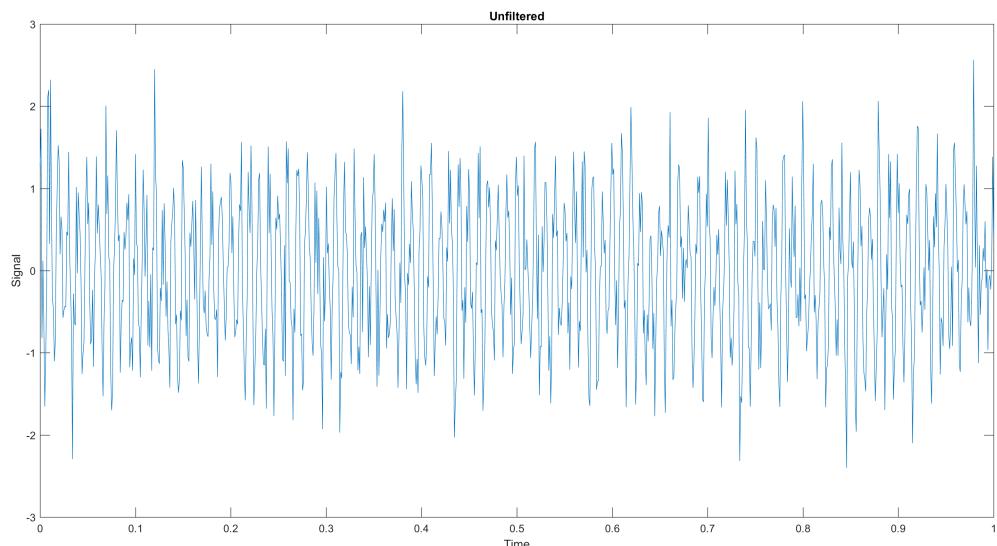
IIR has an advantage respect FIR filters, regard to the filter order. An IIR filter has a very lower order than FIR, so the computations can be done faster. However, its phase response is not linear like the FIR's response. The physical meaning of this is if a signal is passed through this filter, different frequency components of this signal will be delayed by different lengths of time, causing distortion. There is a way to overcome the problem of having a non-linear phase with the IIR filter. Filter the signal, time reverses the signal, and filter it again with the same filter. A MATLAB command (*filtfilt*) allow us to perform this operation.

Low Pass Filter

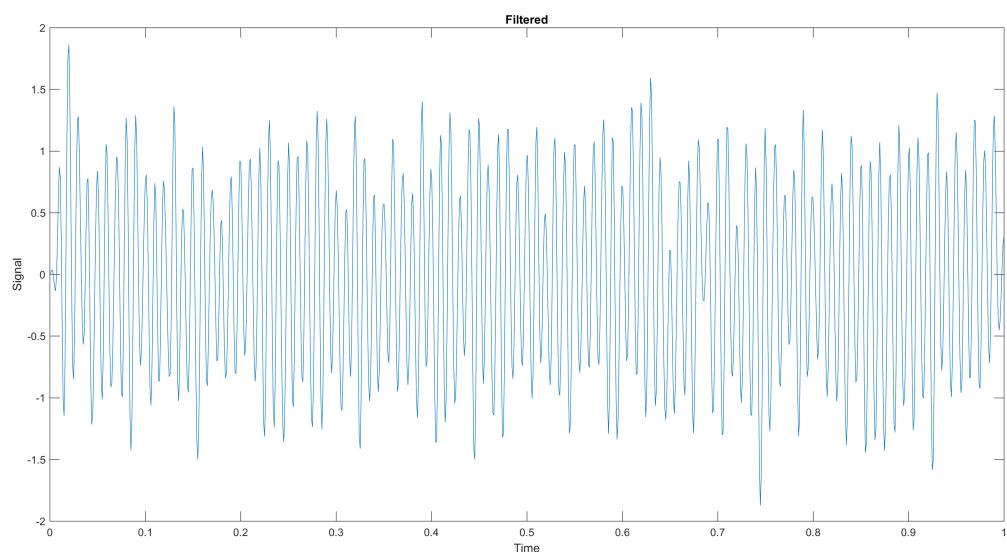
A Low-Pass Filter is a filter that allows the passage of signals below a cutoff frequency (known as the passband) and attenuates signals above the cutoff frequency (known as the stopband). The exact frequency response of the filter depends on the filter design. A low-pass filter is the complement of a high-pass filter. Through removing some frequencies, the filter creates a smoothing effect. The filter produces slow changes in output values to make it easier to see trends and increase the signal-to-noise ratio with minimal signal degradation. Low-pass filters provide a smoother form of a signal, removing the short-term fluctuations, and leaving the longer-term trend. Low-pass filters, especially moving average filters or Savitzky-Golay filters, are often used to smooth signals, remove noise, perform data averaging. Other common design methods for low-pass FIR-based filters include Kaiser window and equiripple. Design methods for IIR-based filters include Butterworth, Chebyshev (Type-I and Type-II), and elliptic. Below is shown an example of application of Low-Pass-FIR filter on a Signal, with a Sample Rate of 1000 Hz and a Cutoff Frequency of 150 Hz .



(a) Filter Response



(b) Unfiltered

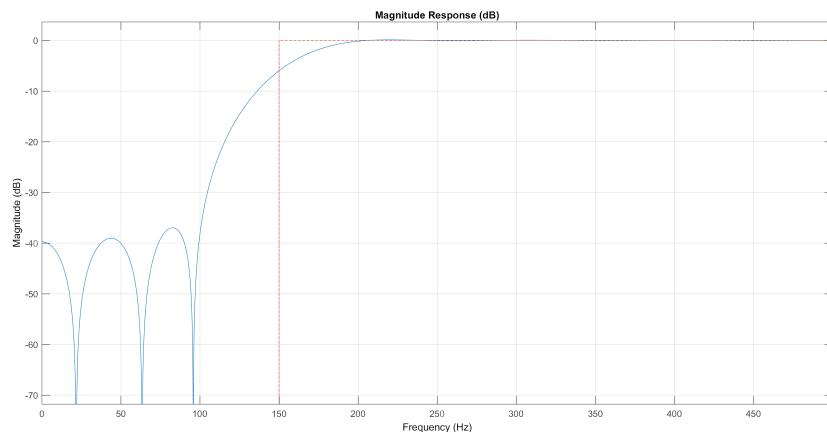


(c) Filtered

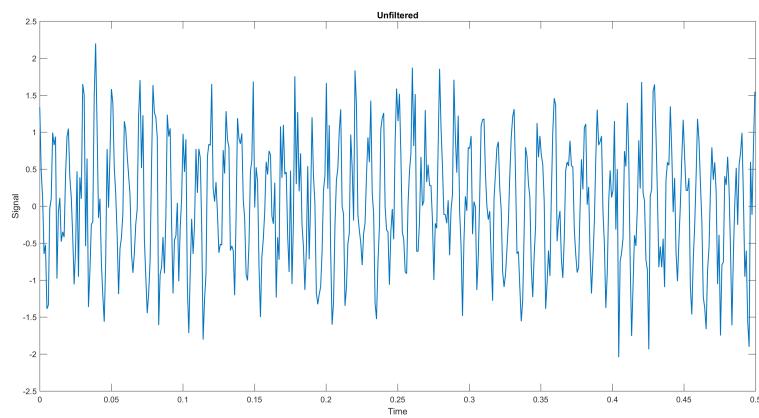
High Pass Filter

A high-pass filter attenuates signals below a cutoff frequency (known as the stopband) and passes signals above the cutoff frequency (known as the passband). The amount of attenuation for each frequency depends on the filter design used. It is the complement of a low-pass filter and they can also be used in conjunction with a low-pass filter to produce a bandpass filter. High-pass filters are often used to smooth low-frequency noise and remove low-frequency trends from time series data highlighting the high-frequency trends. Common design methods for high-pass FIR-based filters include Kaiser window, least squares, and equiripple. Design methods for IIR-based filters include Butterworth, Chebyshev (Type-I and Type-II), and elliptic.

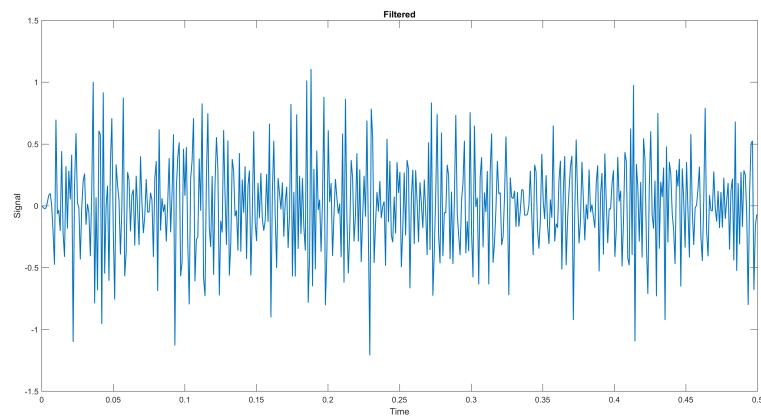
Below is shown an example of application of High-Pass-FIR filter on a Signal, with a Sample Rate of 1000 Hz and a Cutoff Frequency of 150 Hz .



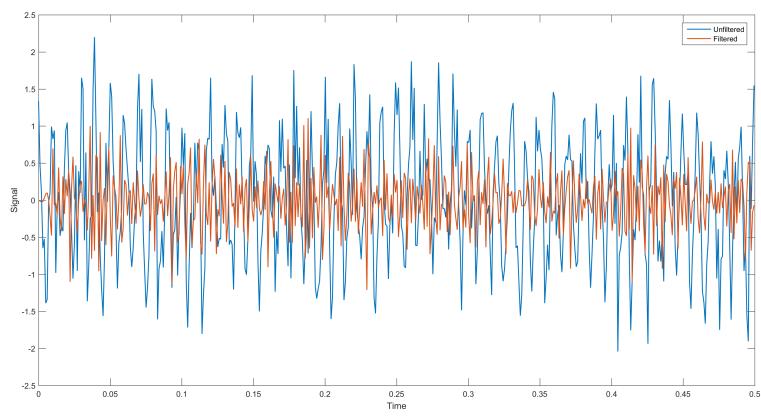
(a) Filter Response



(b) Unfiltered Signal



(c) Filtered Signal



(d) Signal Overlapping

The original signal (b) is represent in blue, the filtered signal is represent in orange (c).

Figure 4.9: Example of Application of High Pass Filter

Band Pass Filter

A band-pass filter is a filter that passes frequencies within a certain range and attenuates frequencies outside that range. The filter can be designed to perform this task by combining the properties of low-pass and high-pass into a single filter. The ideal band pass filter has a perfectly flat bandpass, does not attenuate the frequencies inside, and completely attenuates all frequencies outside of this range. In practice, no band pass filter is ideal. The filter does not completely attenuate all frequencies outside the desired bandwidth. Between the lower frequency f_1 and the higher f_2 of a band pass, is located the resonance frequency, in which the filter gain is maximum. The filter's bandpass is simply the difference between f_2 and f_1 .

Below is shown an example of the Response of a Band Pass Filter with lower frequency $f_1 = 250\text{ Hz}$ and higher frequency $f_2 = 550\text{ Hz}$.

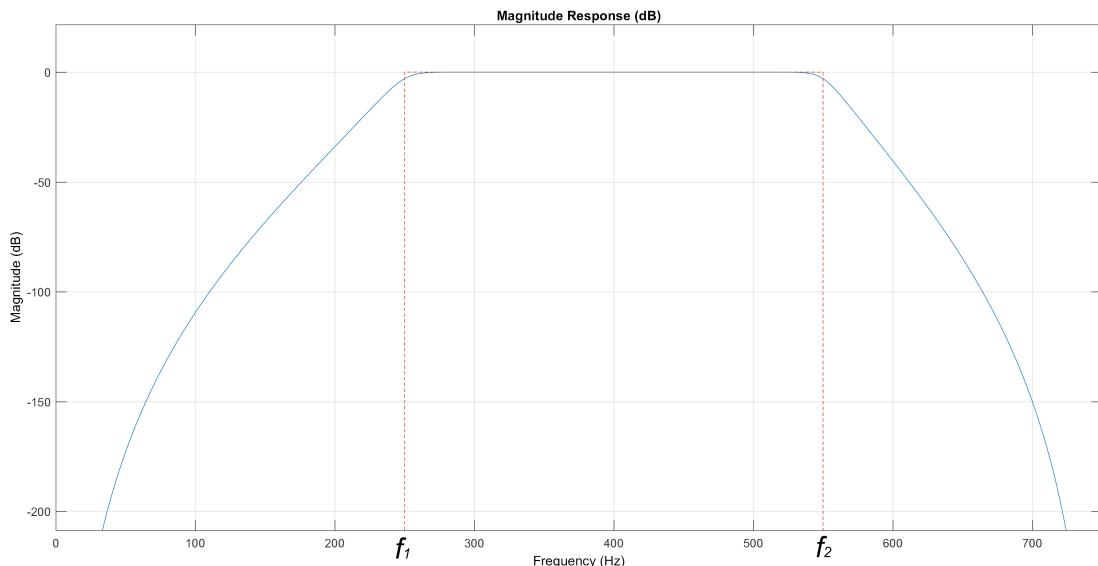


Figure 4.10: Band Pass Filter Response

4.3 Fast Fourier Transform

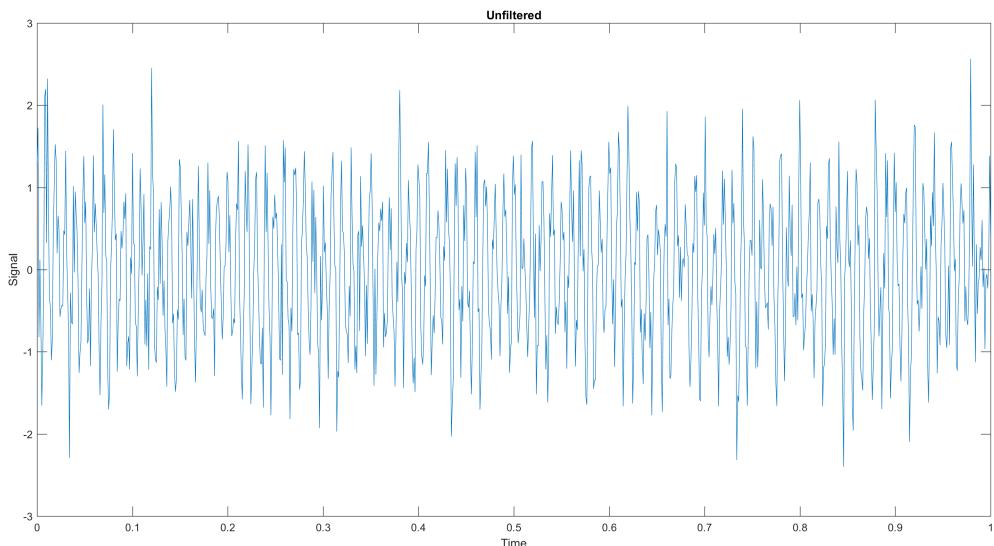
Various data filtering techniques have been analysed but in order to understand in which frequencies we find the signal disturbance, and so choose the cutoff frequency properly the Fourier Transform can be used. The Fourier Transform is a mathematical technique widely used in science, engineering and digital signal processing. The mathematical technique called the Discrete Fourier Transform (DFT) takes a discrete time series of n equally spaced numbers and transforms or converts this time series through a

mathematical operation into a set of n complex numbers defined into the frequency domain from the time domain. DFT is an extremely powerful mathematical tool that allows to view signals in a different domain, inside which several difficult problems become very simple to analyse respect the original time series, in which is computationally hard to do. If the time series is made up of oscillating signals of various frequencies plus noise, in the frequency domain we can find frequencies we have no interest and also find the noise content of the price data.

To check this, compute the DFT m of Signal and see what it looks like in the frequency domain. The Fast Fourier Transform (FFT) is a mathematical algorithm that computes the DFT very fast. The DFT formula:

$$X(m\omega_s) = \sum_{k=0}^{N-1} x_k e^{-jm\omega_s k} \quad \text{where} \quad \omega_s = \frac{2\pi}{N} \quad (4.10)$$

Computed this it is possible to see if a spectral peak is present. For this purpose, MATLAB has the *fft* function, which performs the DFT computation4.3 in an efficient manner, it is called the Fast Fourier Transform (FFT). Hand it a vector x of time domain samples, and it returns a vector X of samples $X(m\omega_s)$, $m = 0, 1, \dots, N - 1$ of the DFT computation. If we take for example this signal:



And compute the *fft*:

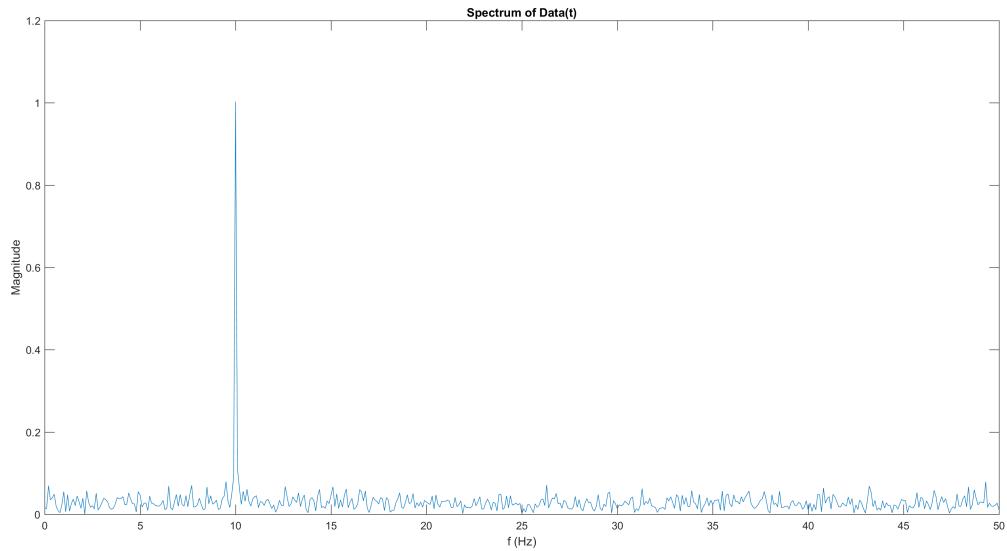


Figure 4.11: Fast Fourier Transform

It is possible see that there is a peak around 10 Hz . This frequency can be used like cutofffrequency to filtering out the noise, depends the filter you want to use, like Low Pass Filter4.2.2, or High Pass Filter4.2.2.

4.4 GPS points division

Another problem to fix is the way geolocation points are identified. As discussed in Chapter3 , (GPS section3.3, on a page: 31), GPS records the data at a frequency of 1 Hz (every second), however, the acceleration data as we have seen in our case are recorded at 100 Hz (every 10 ms). For every GPS recording, 100 acceleration data will be registered. This puts us in front of a problem because if we want to map the road surface correctly, GPS data need to be very close to each other. To understand better this factor, two different GPS coordinates were identified:

$$\text{Start} = (\text{Latitude}_{\text{start}}, \text{Longitude}_{\text{start}})$$

$$\text{End} = (\text{Longitude}_{\text{end}}, \text{Longitude}_{\text{end}})$$

show on the figure below:

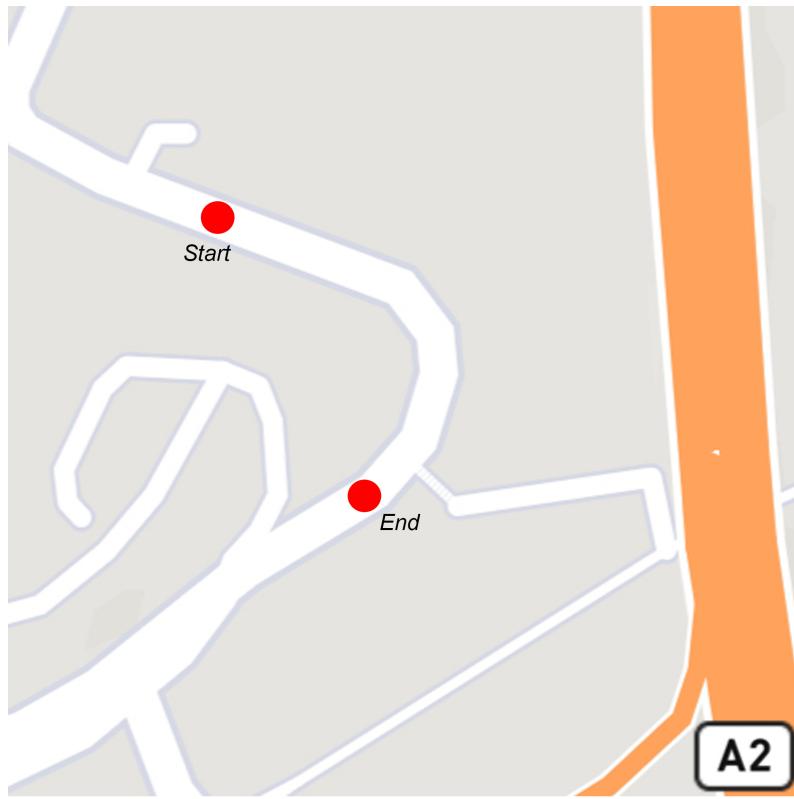


Figure 4.12: Start and End points

As we can see, we have two different GPS points, but we have a data accumulation at the *Start* point, in our case equal to 100 measurements and each of these has *Start* point as GPS coordinate, the situation is analogue to the *End* point. Start point recordings refer to all *Start – End* segment, but the intermediate coordinates of the segment are not recorded, and that is what is needed to properly locate the road surface conditions. Therefore, a methodology has been developed, which from two different GPS points, allows determining the intermediate points in the segment. As shown in the Matlab code below.

```

redefineLatitudeAndLongitude ( ReadedLatitude , ReadedLongitude )

NewLatitude = zeros(1 , 1);
NewLongitude = zeros(1 , 1);
i = 1;

for y = 2: numel( ReadedLongitude )
    lation1 = [ ReadedLatitude(i ,1) , ReadedLongitude(i ,1) ];

```

```

latlon2 = [ ReadedLatitude(y,1) , ReadedLongitude(y,1) ] ;

distance = lldistkm( latlon1 , latlon2 ) ;

if ( distance ~= 0 )
    LatitudeDifference =
        ReadedLatitude(y,1) - ReadedLatitude(i,1) ;
    LongitudineDifference =
        ReadedLongitude(y,1) - ReadedLongitude(i,1) ;
    steps = y - i ;

    NewLongitude(i,1) = ReadedLongitude(i,1) ;
    LongitudeToAdd = LongitudineDifference / steps ;
    for ix = i+1:y-1
        NewLongitude(ix,1) = NewLongitude(ix-1,1)+LongitudeToAdd ;
    end
    NewLongitude(y,1) = ReadedLongitude(y,1) ;

    NewLatitude(i,1) = ReadedLatitude(i,1) ;
    LatitudeToAdd = LatitudeDifference / steps ;
    for ix = i+1:y-1
        NewLatitude(ix,1) = NewLatitude(ix-1,1)+LatitudeToAdd ;
    end
    NewLatitude(y,1) = ReadedLatitude(y,1) ;

    i = y ;
    end
end

```

Code to divide the point inside a segment.

The proposed algorithm, when distinguishing two points having a distance between them different from 0 km, calculated by the *haversine formula* 4.4.1 that will be explained later, begins the definition of intermediate GPS points in the segment. Beginning

from the *Start* point, until to the *End* point, all intermediate points for both Latitude and Longitude will be calculated, as the previous point plus the difference in Latitude between the Start point and the End point, divided by the number of occurrences between Start and End, analogue procedure for Longitude.

Final result is shown in the figure:



Figure 4.13: Start and End points

4.4.1 Haversine Formula

This formula is particularly useful because it allows calculating the geographical distance between two points. Particularly in our case, it is mainly used for:

- Determine if there is a not null distance between two geographic points, so that the segment can be subdivided.
- Applied during the data processing, since following the subdivision, all consecutive geolocation points will have a very small distance. For example, if we go at very low speeds, and take two consecutive points, their distance can be measured in the order of *cm*, otherwise, at very high speeds, the distance between the points are usually measured approximately in the order of a few *mt*. The points to be correctly displayed on the map must be at a specified distance ($distance_{th}$) from each other. It will be checked from an initial point *Start*, what are all the points that gradually adding their distances to each other, reaching $distance_{th}$, so a new point is created, and all those considered to arrive at $distance_{th}$ are eliminating (for acceleration values, however, different operations are performed depending on the index being calculated). This operation will be repeated for all points in the data set until we will have each point distant from each other by $distance_{th}$.

Haversine Formula calculates geographic distance on earth. Given two different latitude – longitude values of two different point on earth, then with the help of Haversine Formula, it is easily possible compute the great-circle distance (The shortest distance between two points on the surface of a Sphere). The haversine formula is defined like follow:

Given two points:

$$Start = (\phi_1, \lambda_1)$$

$$End = (\phi_2, \lambda_2)$$

where:

- ϕ represent the *Latitude*.
- λ the *Longitude*.
- r is the radius of the earth.

- d the distance between the two points.

$$\text{hav} \left(\frac{d}{r} \right) = \text{hav} (\phi_2 - \phi_1) + \cos(\phi_1) \cos(\phi_2) \text{hav}(\lambda_2 - \lambda_1)$$

hav is the haversine function defined:

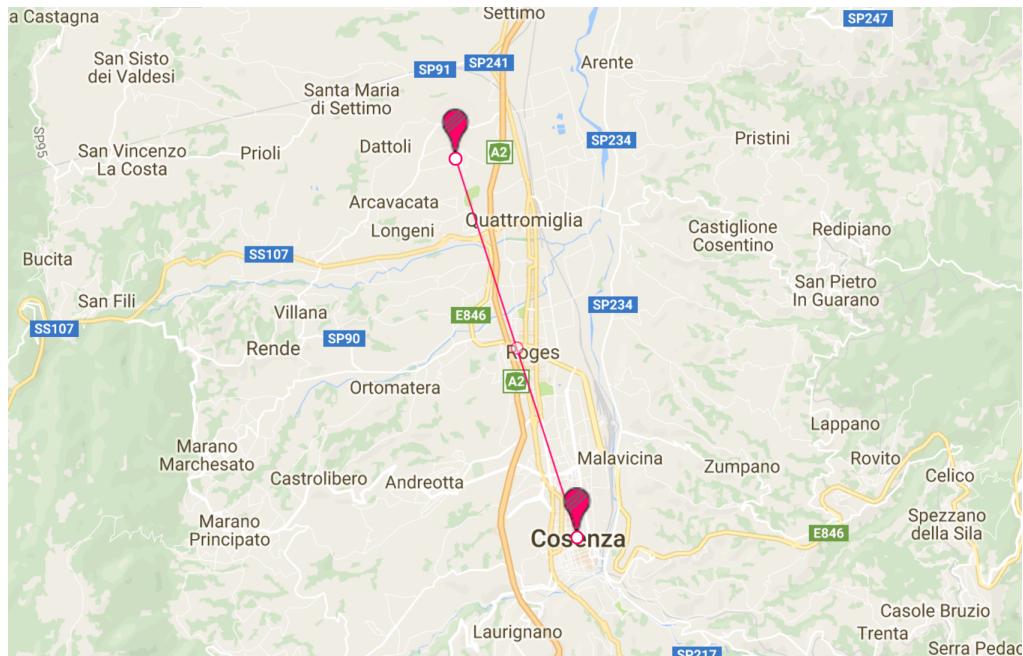
$$\text{hav}(\theta) = \sin^2 \left(\frac{\theta}{2} \right)$$

The sign $\frac{d}{r}$ is the central angle, assuming angles are measured in radians (note that ϕ and λ ; can be converted from radians to degrees by multiplying by $\left(\frac{180}{\pi} \right)$). Solve for d by applying the inverse haversine (if available) or by using the arcsine (inverse sine) function, the distance is calculated like follow:

$$d = 2r \arcsin \left(\sqrt{\sin^2 \left(\frac{\phi_2 - \phi_1}{2} \right) + \cos(\phi_1) \cos(\phi_2) \sin^2 \left(\frac{\phi_2 - \phi_1}{2} \right)} \right)$$

The distance result is can represent in $\text{km}, \text{mt}, \dots$ depending on the unit misure of r .

The figure below shown an example of application of Haversine Formula, to calculate flying distance from Universita' della Calabria to Cosenza.



In this example the flying distance is 7.13 km

Figure 4.14: Haversine Example

5

Road Surface Analysis

This chapter describes the techniques that have been used, focusing on the following topics:

- How data are collected.
- Preprocessing and surface condition indexes computation.
- Storage and Integration of processed data.
- Indexes visualization on a map.

The figure below shows the structure of the system.

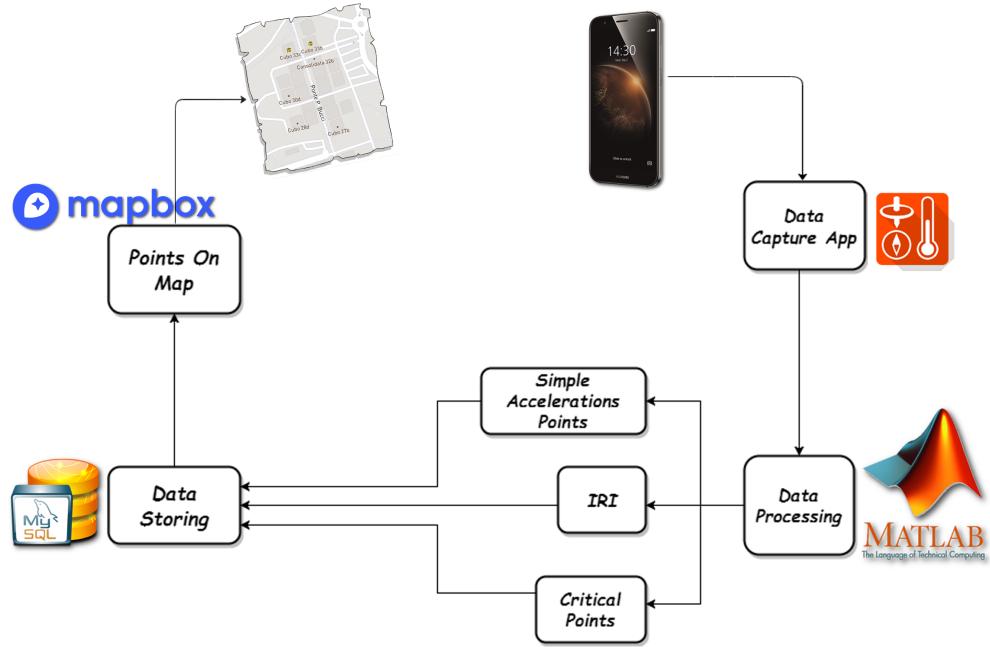
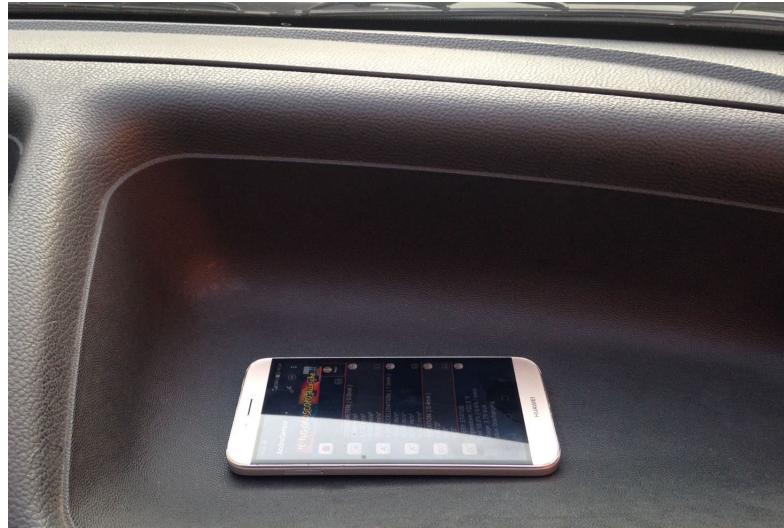


Figure 5.1: System Structure

5.1 Data Collection

Initially, the smartphone was fixed up at the windshield of the car by an arm support, forming a 90-degree angle between the phone and the vehicle axes. However, during travel, the support was subject to vibrations that caused additional noise in the data, and could also be subject to movements due to the nature of the support itself and the road surface conditions, thus changing the integrity of the data. The smartphone was then mounted horizontally on the car dashboard, forming a proximal 0-degree angle with it, using a non-slip material. This setting was optimal because the perceived vibrations by the sensor are proportional to the vibrations experienced by the car's chassis, meaning that the movements of the smartphone itself were sufficiently small. The **AndroSensors** application available on the PlayStore was adopted as software for interacting with the sensors. That allows us performing multiple concurrent measurements of various sensors.



(a) Side view



(b) View from above

Figure 5.2: Smartphone positioning on car dashboard while recording data.

For our analysis, data was gathered from the following sensors:

- Accelerometer.
- Linear Accelerometer.
- GPS.
- Orientation.
- Date
- Time

The data are updated at the highest frequency "*Very Fast*", while the sampling frequency can be chosen within a range that goes:

$$\begin{aligned} fs_{min} &\leq f_s \leq fs_{max} \\ 200\ Hz &\leq f_s \leq 1\ Hz \\ 0,005\ s &\leq f_s \leq 1\ s \end{aligned}$$

Choosing a very low sampling frequency (for example, fs_{min} , sensor values may be inconsistent at writing time due to their fast sampling frequency. However, the higher is the sample rate, the better the final result of our analysis is since it can work on more samples and reduce the overall error. Conversely, choosing a very high sampling frequency, (for example, fs_{max}), we will have very disconnected data, in fact, travelling at a speed of $130\ km\ h^{-1}$, data would be collected every $36,11m$, which is not favourable to the monitoring of road surface conditions. Because of these reasons, the sampling frequency was fixed at the following value:

$$fs = 100\ Hz; \quad fs = 0,01s; \quad fs = 10ms$$

Which is stable, and for every second of recording, 100 samples are collected. On the adopted hardware, unfortunately, the GPS sensors cannot sample at frequencies lower than $1\ Hz$ (there are smartphones that are capable of reaching $20\ Hz$). Once the GPS signal has been established, it is possible to start recording the data.

5.2 Data Processing

Regarding data processing, 3 indexes will be extrapolated:

- Simple Accelerations Points
- Critical Points
- IRI

Once the measurements are complete, the data will be saved in a *.xls* file. These will be processed with MATLAB (Matrix Laboratory) a multi-paradigm numerical computing environment, which makes numerical computing more easier and computationally faster than other programming paradigms. Initially, the *.xls* file is read, and each column of it depending on the data nature (numeric or string) will be stored in a

vector, which can be found in the MATLAB workspace. Once the raw data has been read, the indexes computation starts.

5.2.1 Simple Acceleration Points

This index helps principally to show how the acceleration component changes depending on different points on the road surface. It notes that an appropriate methodology is needed to calculate the surface conditions because the representation of the acceleration signal alone would not be satisfactory to provide all the conditions of a given road segment. This index will be calculated on a segment of a predetermined length ($distance_{segment}$, from now it is called ds) in which an χ value will be associated and calculated as follows:

$$\chi = \left(\sum_{i=1}^N a_i \right) \frac{1}{N}$$

where:

- N is the number of GPS points necessary to reach a lenght of ds
- a_i is the processed acceleration value associated to i

For example, considering a urban road in good conditions, the travel speed is low, so for each considered segment, the number of samples collected per second is high. This means that the final result is obtained averaging many points. High energy peaks are smoothed by low energy samples by which are outnumbered. The end result will definitely have a small value. This value would indicate that the condition of the road surface it is almost perfect, although it might not be the case. On the other hand, when taking into consideration an highway, the travel speed is high so for each analysed segment, the number of samples available is lower, since the segment is traversed in a shorter amount of time. High energy peaks are not outnumbered by the low energy peaks so the resulting in a higher computed value, which should suggests that road surface conditions is not optimal.

For each considered segment the proposed indexes is computed performing the following steps:

For example considering the following signal:

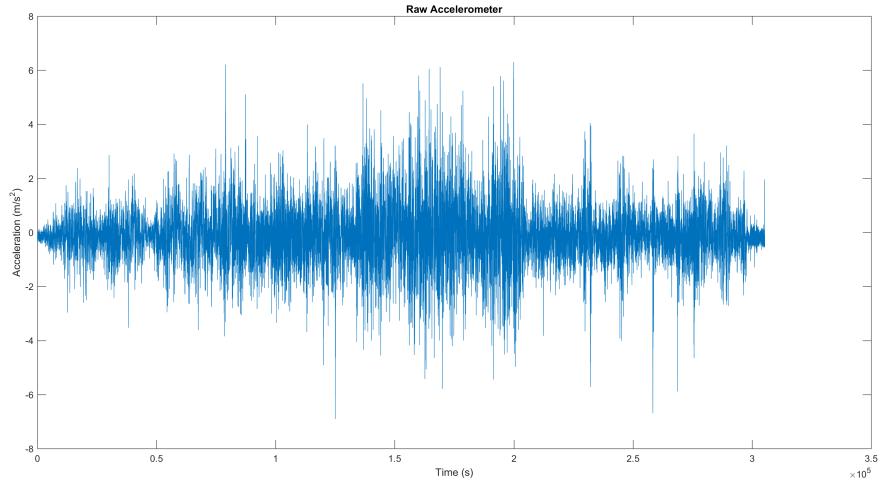


Figure 5.3: Raw Accelerometer Signal

The steps are as follows:

- 1. Accelerometer Reorientation:** First of all it is applied the procedure of Accelerometer reorientation explained in Chapter4 (section:4.1, on page: 40).
- 2. GPS points division:** Next, the GPS points are subdivided according to the methodology explained in Chapter4 (section:4.4, on page: 54).
- 3. Filtering Engine Vibrations:** This filter is the first operation that is performed on the data, in which the noise components generated by the engine will be smoothed, according to the application seen in the Chapter4 (section:4.2, on a page:42) A figure below shows how the filter is applied on the Signal

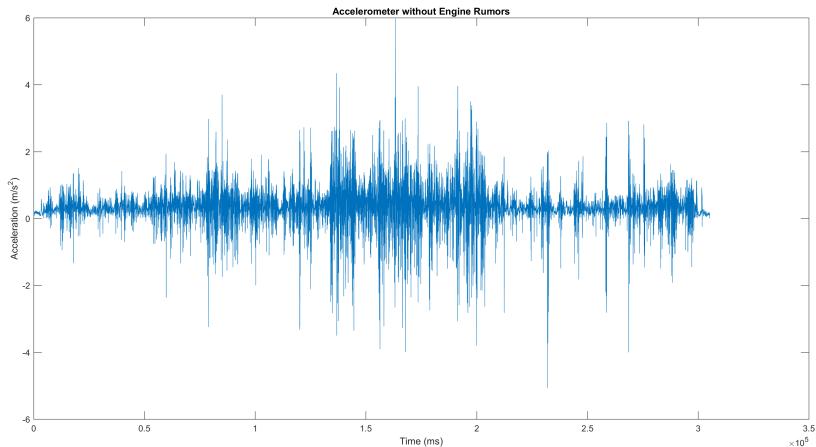


Figure 5.4: Signal after application of the filter

4. Zero Velocity Filter: After applying the first filter, this is also applied, as it is explained in the Chapter4 (section:4.2, on page:44). A figure below shows how the filter is applied on the Signal

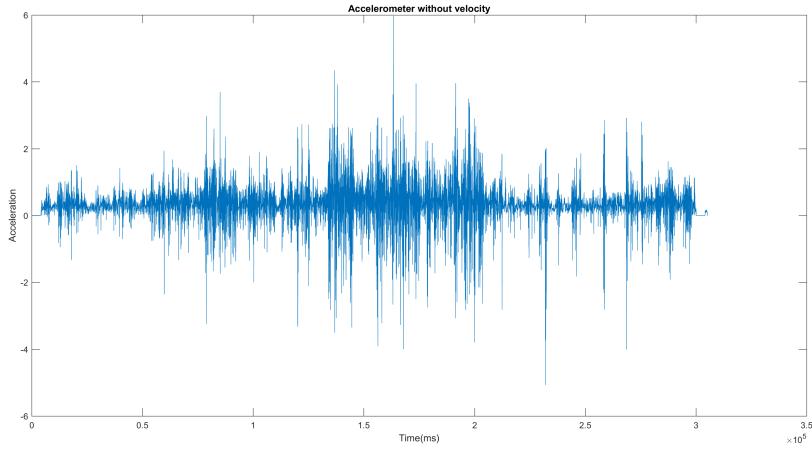


Figure 5.5: Signal after application of the filter

5. Calculation of the final index: Ultimately, the final index is calculated. This value it is associated with a certain portion of the road (ds). Following the application of the two previous filters, the Haversine formula will be used (as it is explained on a page: 4.4.1) to calculate the cumulative GPS distance of points until the ds is reached. The new GPS point will be identified by the set of points needed to compose the segment. For the χ 5.2.1 value, it will be calculated by all the acceleration values that are simultaneously read together with GPS points.

A figure below show the result.

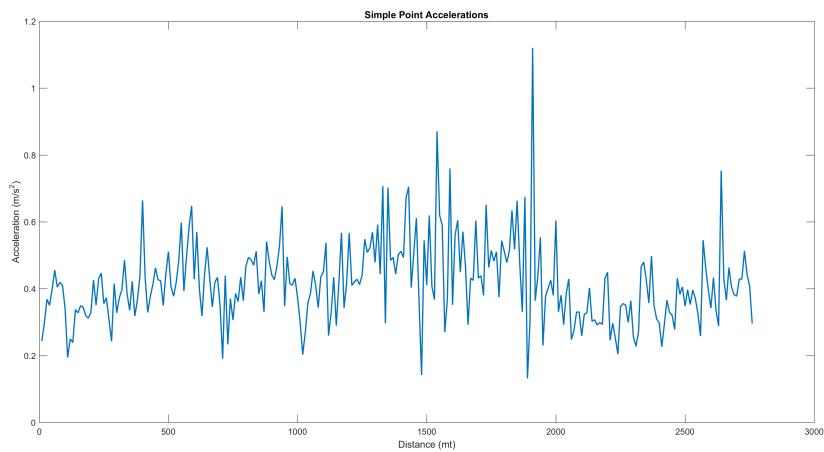


Figure 5.6: Final Result

5.2.2 Critical Points

This index is very useful as it allows us to locate the most damaged points on the road surface. Allowing us to identify holes, bumps, and all those types of anomalies that passing over one of them could damage the vehicle and cause an inadequate feeling level of comfort at the driver 1. For this, being informed of the localisation of these anomalies, allows the driver during navigation, to avoid them or reduce speed in their proximity. This index is processed and calculated only by the vertical acceleration signal because the presence of high peaks corresponds to high-energy events generated by the road-vehicle vibration and can, therefore, be associated with "anomalies" on the surface. Each of these points will be properly geolocated on the Earth's surface, as for the other indexes, also in this case, at each acceleration signal, GPS coordinates will be associated.

Following the processing of the signal, which will be properly smoothed, in order to identify the critical points, the final value will be calculated as follows:

$$\begin{aligned}\kappa_i &= 0 \quad \text{if } threshold_{min} \leq a_i \leq threshold_{max} \\ \kappa_i &= a_i \quad \text{if } a_i > threshold_{max} \quad \text{or} \quad a_i < threshold_{min}\end{aligned}$$

where:

- κ_i is the index results.
- a_i is the acceleration signal.

Following several inspections and controls on the signal, it was possible to identify two thresholds ($threshold_{min}$, $threshold_{max}$). If the signal falls within this range then it does not correspond to an anomaly, vice-versa if it is outside it, represent an anomaly.

Considering the following signal:

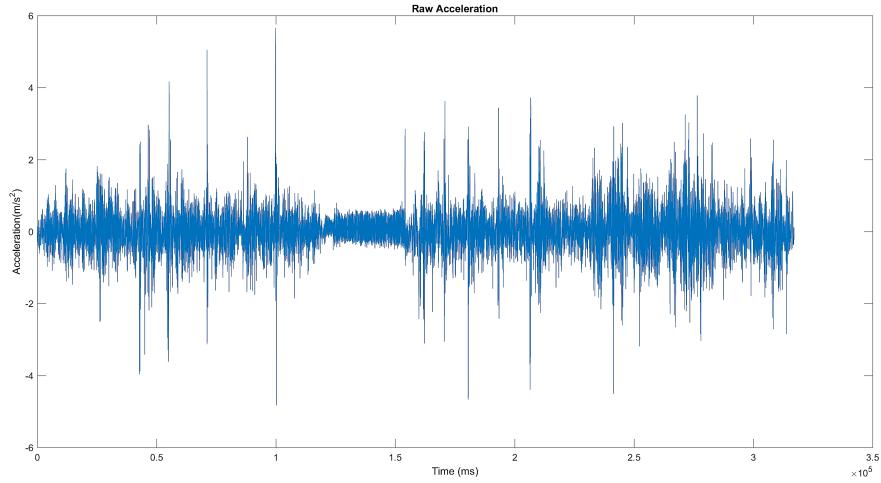


Figure 5.7: Original Signal

The steps for its calculation are:

- 1. Accelerometer Reorientation:** First of all it is applied the procedure of Accelerometer reorientation explained in Chapter4 (section:4.1, on page: 40).
- 2. GPS points division:** Next, the GPS points are subdivided according to the methodology explained in Chapter4 (section:4.4, on page: 54).
- 3. Filtering Engine Vibrations:** This filter is the first operation that is performed on the data, in which the noise components generated by the engine will be smoothed, according to the application seen in the Chapter4 (section:4.2, on a page:42). The result of the application of the filter on the signal shown above is:

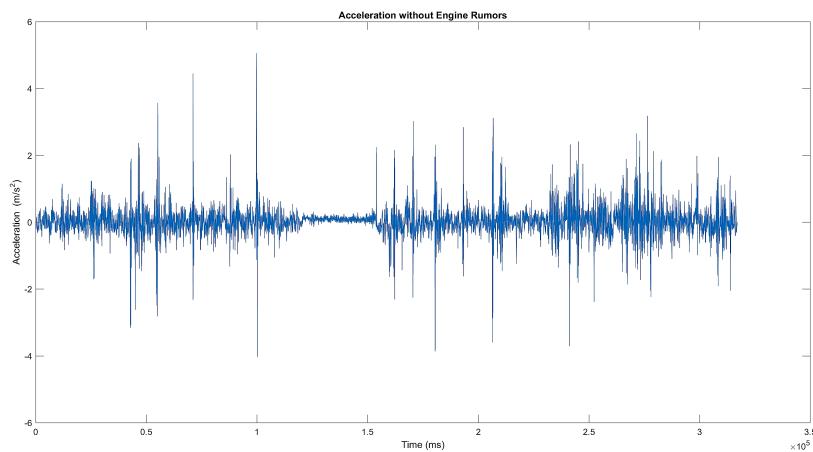


Figure 5.8: Signal Without Engine Vibrations

4. Zero Velocity Filter: After applying the first filter, this is also applied, as it is explained in the Chapter4 (section:4.2, on page:44). The result of the application of the filter on the signal shown above is:

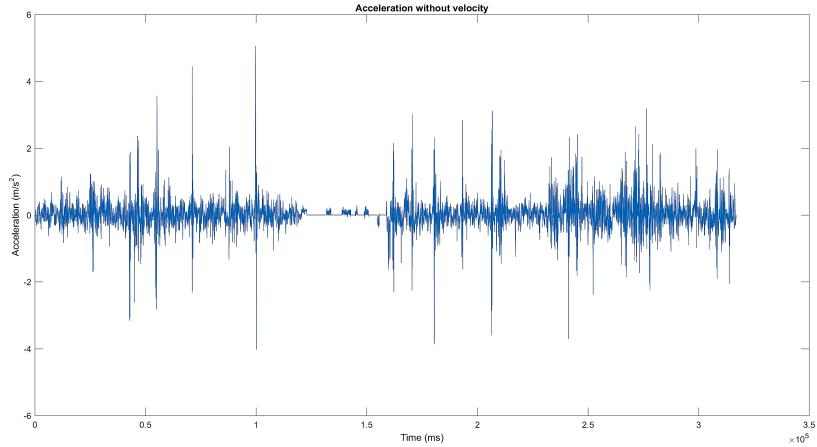


Figure 5.9: Null Velocity Removed

5. Determining Critical Points: In this step, the critical points are identified, according to the formula explained above. The result is shown in the figure. The result of the application of this filter on the signal shown above is:

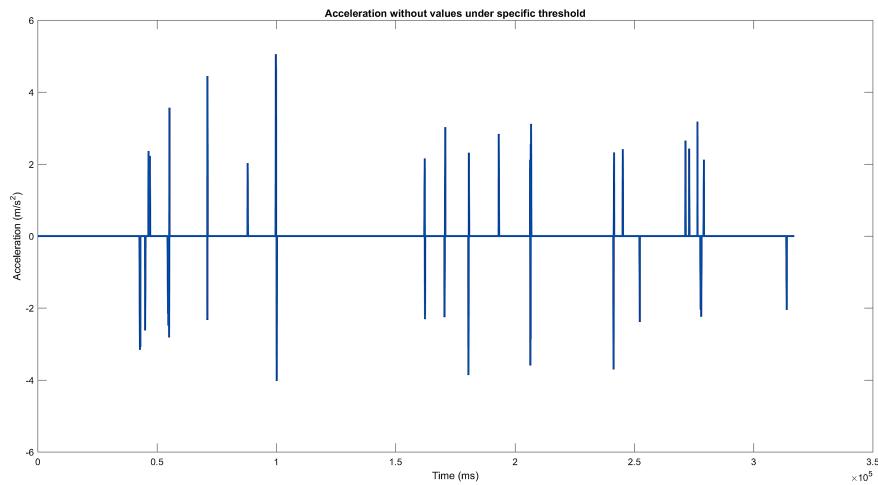


Figure 5.10: Results Final

6. Grouping the points too close each other: Defined the critical points, there is a final step to be carried out. Following the GPS points division(4.4), it may happen in the previous step, that consecutive points are selected, or in any case too close each other, which refers to the same anomaly (in fact, the signal is similar for a given small time due the high recording frequency, so the same anomaly would have more associated signals). It is necessary to incorporate these signals into a single point, for this purpose, the Haversine formula(4.4.1) was used. When a set of points is identified, they will be grouped within a certain distance (ds) and enclosed within a single GPS point. Similarly to the final κ value, it will be identified as the average of the points belonging to this set, because they refer to the same anomaly and will have similar values.

5.2.3 IRI

As we have seen in Chapter2 (on page, 10), where this index is widely explained and how it is calculated. Briefly, represents the most used road roughness index to evaluate and manage road infrastructure. IRI is defined as the ratio between the sum of vehicle-wheel displacements of a standard vehicle. It will be determined following several steps:

- Double integration of acceleration.
- Calculation of IRI from obtained displacement data.
- Correlation phase.

Double Integration Process

The first step to obtaining an index estimate concerns the dual integration of the vertical acceleration signal, useful in achieving vertical displacement. This process as we have seen in Chapter3 may be complex, because the data captured may suffer from various errors (Section 3.4, on page 34) that are accumulating during the travel. In order to obtain an approximate realistic result, it is necessary to perform several data filtering operations (Section4.2 on page 42) in order to remove both, noise components and the drift.

Taking the following signal as an example:

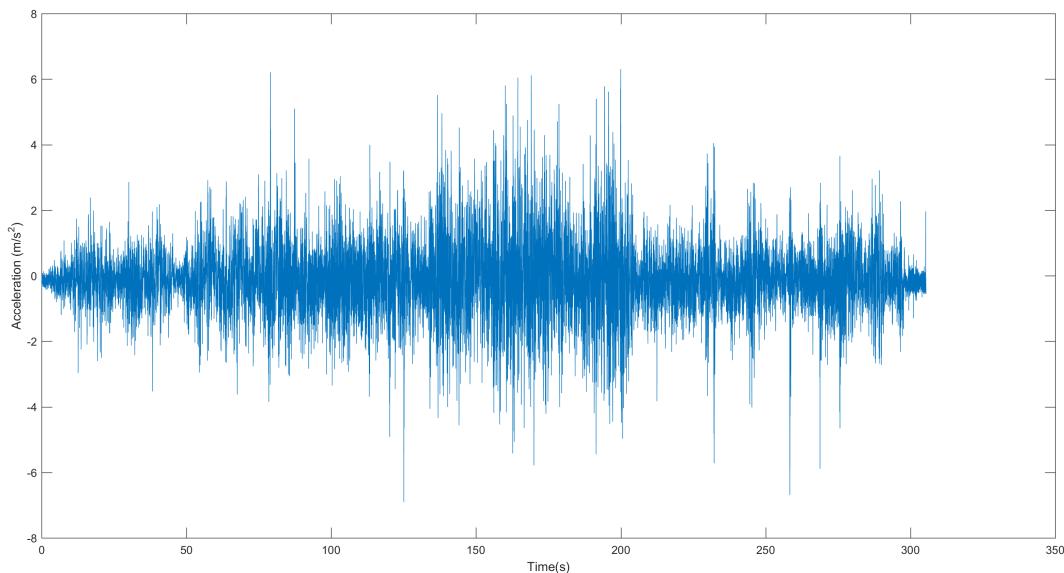


Figure 5.11: Raw Acceleration Signal

The double integration process will be carried out as follows:

- 1. Accelerometer Reorientation:** First of all, it is applied the procedure of Accelerometer reorientation explained in Chapter4 (section:4.1, on page: 40).
- 2. GPS points division:** Next, the GPS points are subdivided according to the methodology explained in Chapter4 (section:4.4, on page: 54).
- 3. Filtering Engine Vibrations:** This filter is the first operation that is performed on the data, in which the noise components generated by the engine will be smoothed, according to the application seen in the Chapter4 (section:4.2, on page:42).
- 4. Zero Velocity Filter:** After applying the first filter, this is also applied, as it is explained in the Chapter4 (section:4.2, on page:44).
- 5. Application of a FIR moving average filter:** A FIR moving average filter will be applied to the signal according to the principles and features discussed in Chapter4, Section4.2, on a page:46. This filter starts to smooth the signal. The result obtained is shown in the figure:

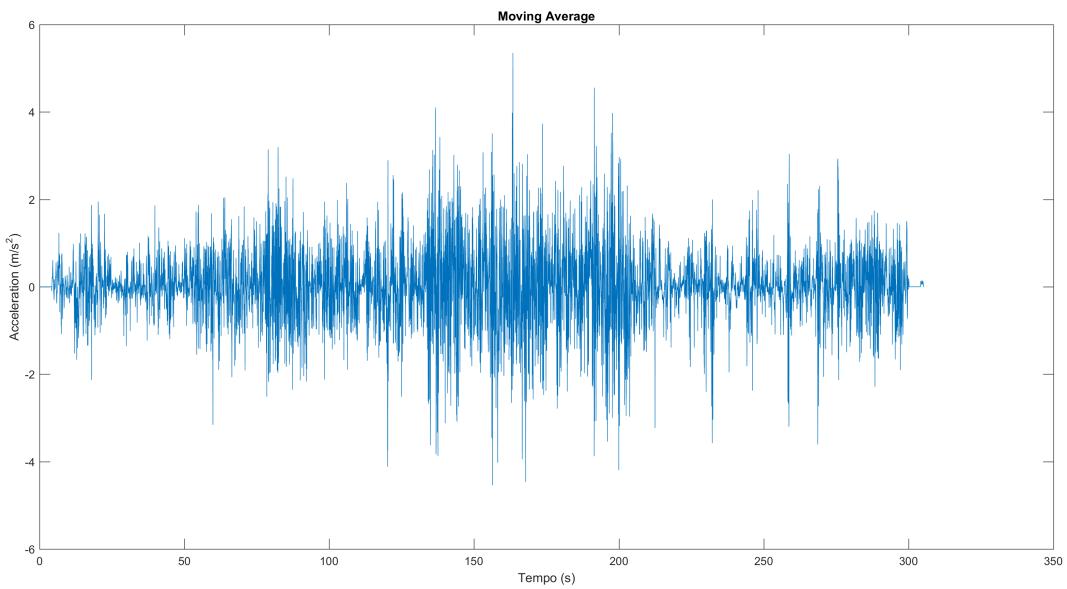


Figure 5.12: Application of a FIR moving average filter on signal

6. Filtering Operations In this phase will be performed the filtering of the signal through the application of two filters. Various Fourier analysis(4.3) were performed on the signals. It emerged that they had various peaks around the frequency of 0 Hz . These values that fall around this frequency are also called DC Components(4.2.2), they cause a high drift(3.4) during the integration phase leading to incorrect results (as shown in the figure4.2). For this reason, it is necessary to eliminate them from the signal. The idea is to allow the passage of the signal that goes over this frequency (more than 0 Hz), and isolate the DC components, around the frequencies of 0 Hz . To do this and for its principles, a High Pass Filter was used, according to the features explained in Chapter4, in section(4.2.2), on a page: 50. Following its application, a Low-Pass Filter will also be used, according to the characteristics described in Chapter4, in section 4.2.2, on a page:48, to smooth the signal without altering his form. After their applications the result obtained is shown in the figure:

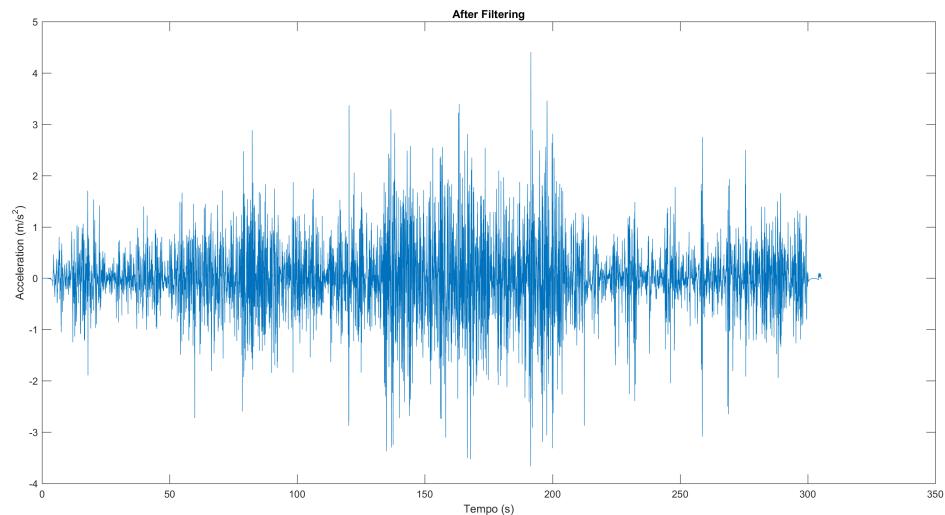


Figure 5.13: Acceleration Signal after the filters application

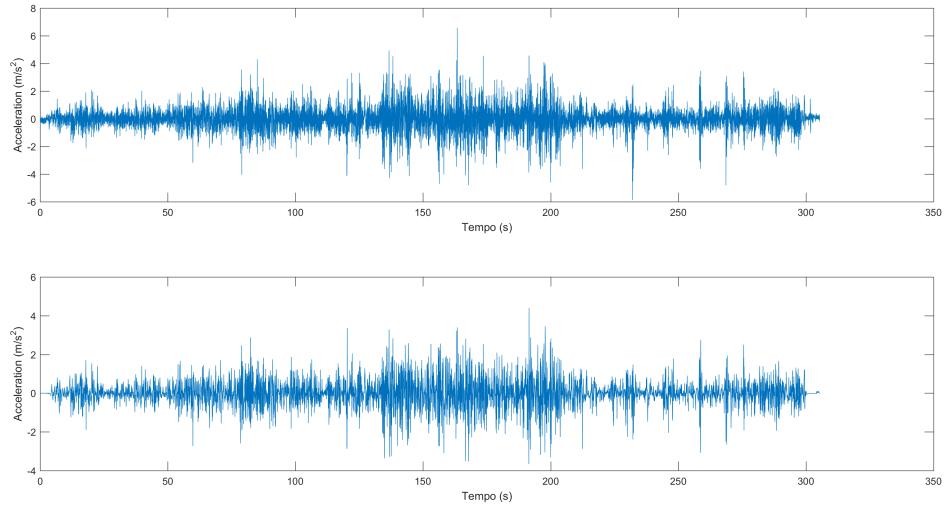


Figure 5.14: Original Signal compared with the filter Signal

While for a more detailed view:

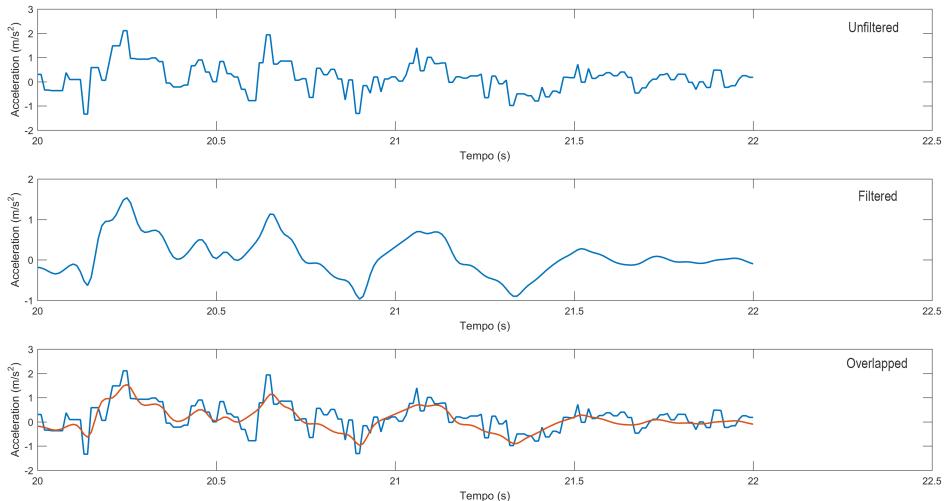


Figure 5.15: Original Signal (blue) compared with the filter Signal (orange) relative to a little set of data

As it is possible to see, the signal now is lighter and significantly smoothed, because DC components were been eliminated and background noise has been reduced.

7. Integration of Acceleration, and filtering velocity signal: After the filtering, the integration of acceleration signal respect to the time(4) can be performed to obtain the speed. For this purpose, the trapezoidal integration method(4) was used. Subsequently, the resulting signal will be subject, for the same reasons

as discussed in step 6, to the same filtering operations. Because during the acceleration integration, the resulting velocity signal will present DC components to be eliminated. The result of integration and filtering is shown on the figure:

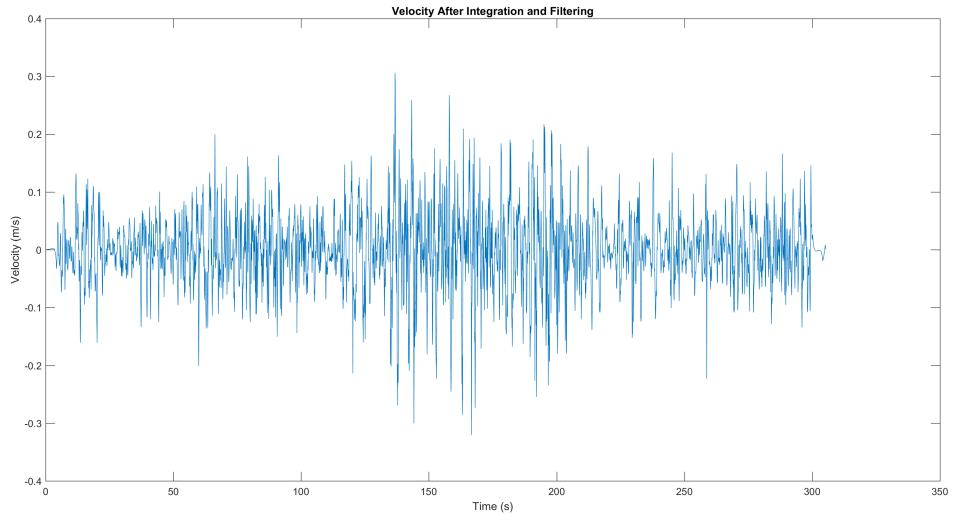


Figure 5.16: Velocity obtained after integration and filtering

8. Velocity Integration: At this point, the integration of the velocity signal respect to the time(4) can be performed to obtain the displacement. Also, in this case, the trapezoidal integration method(4) has been used.

The result of integration is shown on the figure:

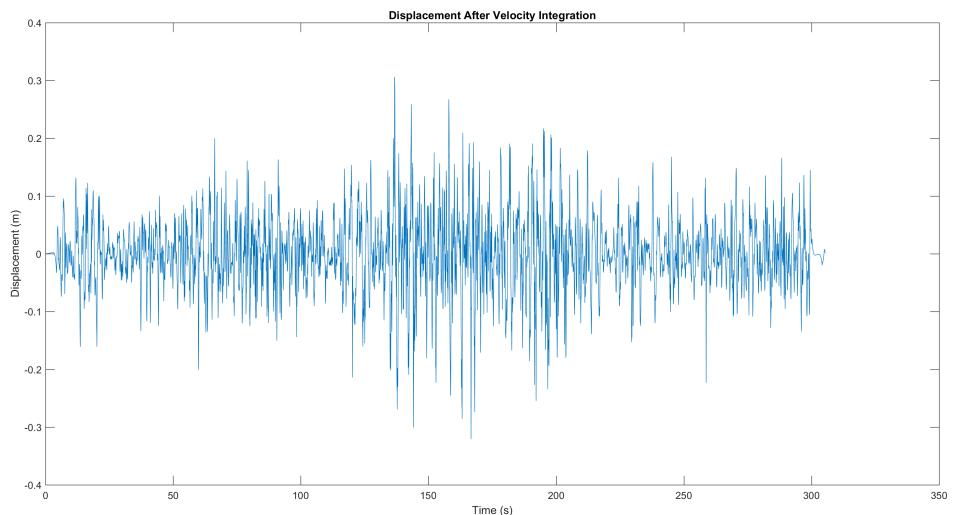


Figure 5.17: Displacement obtained after velocity integration

9. Grouping points in specific distances: Similarly to the other indexes, even, in this case, the displacement points will have to refer each other to a predetermined distance. But, since these data will be processed again to derive an IRI estimate. As indicated 2.4, it is needed a very small segments in order to allow a better accuracy of the result, so the distance between the points, in this case, will be very small.

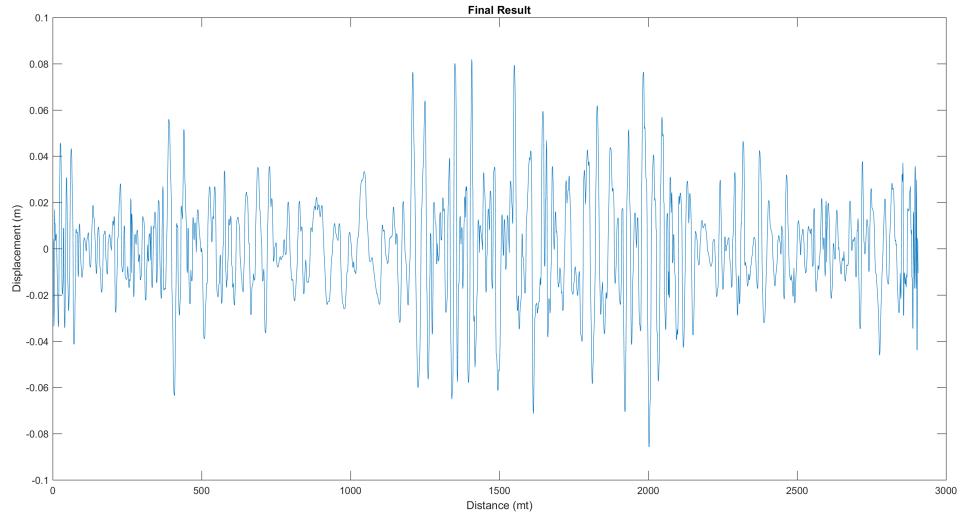


Figure 5.18: Final displacement after grouping points

Calculation of IRI from obtained displacement data

The resulting displacement data will be processed inside ProVal (Profile Viewing and AnaLysis) software to obtain an IRI2 estimate through a simulation of the quarter car model2.3.3. Using Class3 instruments, the value must be calculated for every 100 m + of the road(2.3.1). Inside ProVal, IRI can be calculated in various ways by performing a ride quality analysis:

Overall: Overall calculated on the data series.

Continuos: An IRI threshold is indicated and road sections above this threshold are identified.

Fixed Interval: Calculated on fixed interval road segments.

In our case, it will be calculated on fixed interval which is of 100 m.

Imported the data, the computation will be done by simulating the quarter car model(2.3.3) and applying the IRI Filter(2.4) Below is shown an example of the IRI computation of a data series.

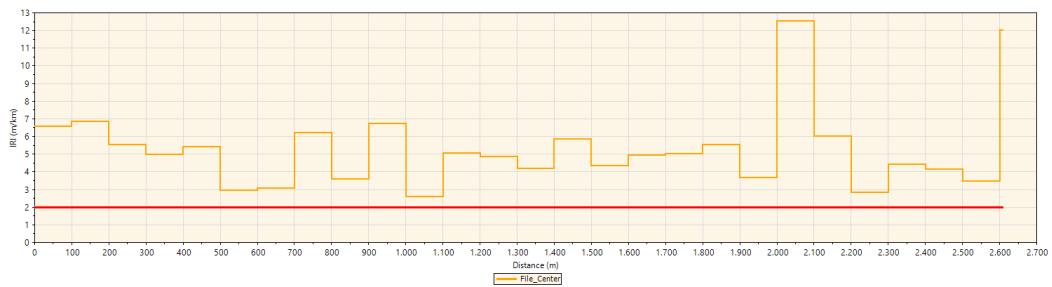


Figure 5.19: IRI computation result

Correlation phase

For these measurement systems, a correlation equation2.3.1 that can be derived from a Class1 or Class2 instruments it is needed, but because we do not own any of them, it has only been simulated.

5.3 Data Storing

After the processing is ended, the results of the respective indexes will be saved on a database by using a Java application where a connection to a MySql database is established using the MySql Connector. For each point of the index in question, they will be stored:

- **Value**
- **GPS coordinates:** in terms of Latitude and Longitude.
- **Registration Date**
- **Point Color**

In the previous chapter⁵, we have seen that each point on the other is separated by a *distance_{fixed}* called *ds*. However, it may happen that some points are close to each other, because if you suppose that the recording is related to road paths that are run on both lanes, some points may be overlap between them or in any case be very close, because of the GPS accuracy (within 10 m) in which the data are stored. A check on the processed data set will be carried out to examine if there are points close to each other within a distance of:

$$\frac{ds}{2},$$

if this happens, a single point will be extracted. Additionally, to each point, a color will be assigned using the HSV color space. This depending on the type of index in question and the value attributed to the point. Generally, a color ranging goes from green (optimal conditions) to red (critical conditions).

To make the read and save faster and more efficacious, a pool of connections was used, in which various threads perform operations on the database. With regard to the insert/update phase, because the data will often refer to the same road sections, it need be checked in this case before insertion, if a point already intersects with a segment referring to points previously saved. If this happens it will be associated with the nearest edge and the value is identified as the average of the two, only updating the point already in the database. Otherwise, if this does not happen a new point is inserted.

5.4 Viewing on interactive map

Finally, processed data will be displayed on an interactive map using the Open Source Mapbox Map. A website for points representation has been developed, in which, each of these is represented by specific color circle using Mapbox APIs.

The density of the points is high. It is, therefore, necessary to have a system capable of clustering them, depending on the zoom of the map display, in fact, if the zoom was low, the points are grouped into larger circles, vice versa if the zoom increases circles they expand until they reach their atomic dimension. The figures below show the start page of the site and an example of the circle clustering associated with the minimum and maximum zoom level.

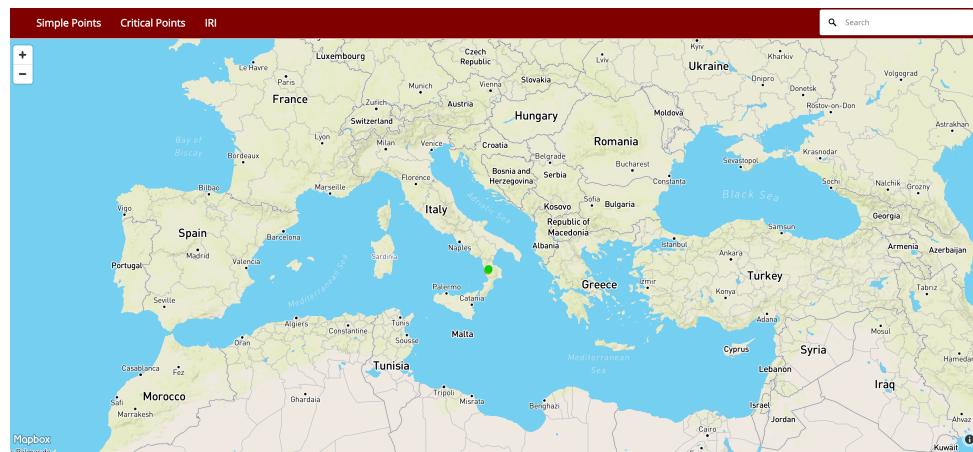


Figure 5.20: Web Site main page



Figure 5.21: Point Clustering based on Zoom Level

As can be seen in the figure:5.4, from the navigation bar it is possible to choose which index will be displayed by clicking on the corresponding button. When is decided to change view by clicking on one of them, an AJAX request will be sent to a Servlet, which queries the database to get the points of the required index, the result is inserted in the AJAX response, from which the GEOJSON (a format for the encoding of different geographic structures) will be created, which will be associated with the map to change the representation layer without reloading the page. It is also possible to search for specific locations from the search bar on the main navigation bar. The specific information of each point is obtainable by clicking on it, where a pop-up is opened, and it shows the registration date and the value associated with that index.

The figure below shows the example of a pop-up.

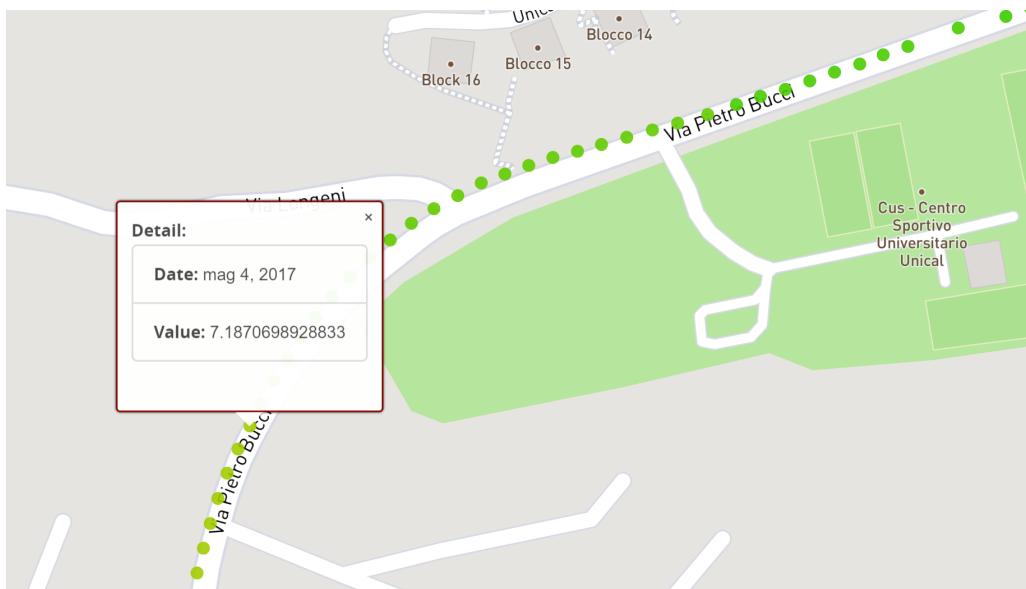


Figure 5.22: Example of PopUp

6

Conclusions and Future Work

6.1 Conclusions

As we have seen in all the previous chapters that are focused to explain the development of the system, the calculations of the various indexes, and problems associated with the monitoring of the road surface conditions, we can deduce that:

- Efficient monitoring systems need very expensive instrumentation as we have seen in Chapter1. However, a monitoring system that collects data from the low-cost sensors, such as using sensors within the smartphone, can be developed.
- The acceleration sensor must be correctly oriented in relation to the vehicle axes, and it can give good values that are closely related to the vibrations perceived by the vehicle with the surface of the road. It has also been seen that, in order to have consistent information over a certain time interval, it is appropriate to identify an appropriate sample frequency to measure the values.

- Subsequently, during processing, an adequate filtering system is required that is strongly dependent on the type of noise the signal is subject to. In order to process it depending on what you want to determine, having useful information, with a minimum level of noise inside the data processed.
- We have also seen that it is possible to calculate a standard reference index, which is the International Roughness Index, obtained from the measurements of Class1 or Class2 instruments, but also by Class3 instruments (as our case) by using an equation of correlation.

Three indexes have been extrapolated from our system:

Simple Accelerations Points: Has provided us with useful information on the acceleration signal resulting from the recordings. It is possible to say that the acceleration signal depending on the amount of information and the type of road in question, without making any sort of intensive filtration operation, but only mediated by a set of points collected within certain distances, we can affirm that it does not provide us any kind of information on road surface conditions. In fact, we saw that apparently, an urban road was more advantageous than a highway. This leads us to understand that we need a mechanism and certain procedural standards for calculating the road surface conditions to obtain a significant index such as IRI.

Critical Points: Instead, it is able to locate accurately the most critical road asperities detected during the signal processing phase. In fact, both on the signal and visual inspections were carried out, to see if it was possible to identify points where bumps, large holes, and other types of anomalies are located and can be directly identified from the signal. And as a result of various information collected, some thresholds have been identified, which provide us with the correct localization of the asperities described and also provide a degree of their danger. Limits (minimum and maximum) have been defined. We can see on the map the different degrees, depending on the color variations to which the respective points are associated. A range of color that swings between orange and red was used to identify these anomalies.

IRI: Has been widely discussed about this index. In Chapter2, we saw what it is and how it is possible to calculate it. It has enabled us to provide, in accordance with its scale, an indication of the quality and comfort level associated with certain road sections. Comprising it is calculated from the vertical displacement between the vehicle and the surface, we have broadly analyzed the problems of double-integration of the vertical acceleration signal, showing the various disturbance and error factors that conduct in incorrect results, and the various steps with it was subsequently determined. This index is usually extracted from measurements made with specific instruments such as profilometers, but it is also possible to detect it by Class3 instrumentation through a correlation equation. It emerged that:

- Despite this instrumentation is not available, the results obtained following the data processing in accordance with the simulation of the quarter car model have provided us good results, compared to the road in question, and moving not much from the IRI scale, indicating the degree of comfort and deterioration of the surface in relation to the result obtained.
- However, a correlation equation for these systems is necessary, because they can shift from the actual level of pavement quality. However, they may not present the need of correlation to certain types of roads, while they need them on others. Since it was not possible to create one, it was only simulated. Although, as previously mentioned, the values obtained represent the degree of damage and comfort of the road surface sufficiently well.

We have described a system for monitoring road surface conditions that can be developed considering a margin of error by making appropriate operations with cheap sensors, compared to most expensive directly related to these procedures.

6.2 Future Work

Inertial sensors are characterised by a constantly evolving and advancing technology, providing the ability to create autonomous systems for understanding and managing data obtained from them. Specifically referring to this scope, the system could be greatly integrated by adding different features.

First of all, the goal is to create a smartphone application that can first make recordings from sensors and send them to a server for their processing. To extend it in such a way as to enable the driver to have a navigation system provided not only to the planned route, but to be informed of the real conditions of the road he/she wants to travel by providing him/her with real-time information based on his/her location.

One point of interest is developing a vocal assistant that can alert us to near critical locations or other types of useful information during the travel.

A future application should allow to choose and display the desired route based on road surface conditions, and also based on current traffic conditions since these IMU also provide other data processing procedures to determine the amount of traffic in some traffic time periods associated with the road sections in question. One could create statistics on average fuel consumption associated with road sections, and choose accordingly.

It is also possible to understand from sensors whether an accident has occurred, so the application may be able to understand it instantly and promptly send a signal to the rescue.

More importantly, with regards to the processing phase for IRI calculation in order to minimise the error level as much as possible, a correlation equation should be identified using an instrument of Class1.

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Bibliography

- [1] ISO 13473-3:2002. “Characterization of pavement texture by use of surface profiles – Part 3: Specification and classification of profilometers”. In: (2012), p. 12. URL: <https://www.iso.org/obp/ui/#iso:std:iso:13473:-3:ed-1:v1:en>.
- [2] ASTM E1364 - 95. “Standard Test Method for Measuring Road Roughness by Static Level Method”. In: (2005).
- [3] AeroStudents.com. “Basic Principles of Inertial Navigation Seminar on inertial navigation systems.” In: *Tampere University of Technology* (2015).
- [4] “Android Sensors”. In: (). URL: <https://developer.android.com/reference/android/hardware/SensorEvent.html>.
- [5] Peter W Arnberg et al. *The laser RST: Current status*. 1991.
- [6] Christopher R Bennett and William DO Paterson. “A guide to calibration and adaptation”. In: *HDM-4. Volume 5. The Highway Development and Management Series* (2000).
- [7] Christopher R Bennett, Hernan de Solminihac, and Alondra Chamorro. *Data collection technologies for road management*. Tech. rep. 2006.
- [8] James Diebel. “Representing attitude: Euler angles, unit quaternions, and rotation vectors”. In: *Matrix* 58.15-16 (2006), pp. 1–35.
- [9] Joint Eapa/Eurobitume Task Group Fuel Efficiency. “Environmental Impacts and Fuel Efficiency of Road Pavements”. In: *Industry Report- March 2004*. (2004).
- [10] Thomas D Gillespie. “Calibration of response-type road roughness measuring systems”. In: (1980).

- [11] Thomas D Gillespie. "Everything you always wanted to know about the iri, but were afraid to ask". In: *The University of Michigan Transportation Research Institute. Nebraska* (1992).
- [12] Robert L Jackson et al. "Synthesis of the effects of pavement properties on tire rolling resistance". In: *NCAT Report* (2011), pp. 11–05.
- [13] R. Colin Johnson. "GPS system with IMUs tracks first responders".
- [14] Michael W. Sayers Steven M. Karamihas. *The little book of profiling*. 1997.
- [15] Prashanth Mohan, Venkata N Padmanabhan, and Ramachandran Ramjee. "Nericell: rich monitoring of road and traffic conditions using mobile smartphones". In: *Proceedings of the 6th ACM conference on Embedded network sensor systems*. ACM. 2008, pp. 323–336.
- [16] W. Paterson and T. Scullion. "Information Systems for Road Management: Draft Guidelines on System Design and Data Issues." In: *The World Bank, Policy Planning and Research Staff, Infrastructure and Urban Development Department* (1990).
- [17] Ires Piemonte et al. *La finanza territoriale in Italia. Rapporto 2012*. Vol. 249. FrancoAngeli, 2013.
- [18] Michael W Sayers. "Guidelines for conducting and calibrating road roughness measurements". In: (1986).
- [19] Michael W Sayers. "Interpretation of road roughness profile data. Final report". In: (1996).
- [20] Michael W Sayers. "On the calculation of international roughness index from longitudinal road profile". In: *Transportation Research Record* 1501 (1995), pp. 1–12.
- [21] Michael W Sayers. "The international road roughness experiment: establishing correlation and a calibration standard for measurements". In: (1986).
- [22] MW Sayers, TD Gillespie, and CAV Queiroz. "The international road roughness experiment: a basis for establishing a standard scale for road roughness measurements". In: *Transportation Research Record* 1084 (1986), pp. 76–85.
- [23] Bruno Siciliano and Oussama Khatib. *Springer handbook of robotics*. Springer, 2016.

- [24] AIPCR - Technical Committee on Surface Characteristics. "Inventory of road surface characteristics measuring equipment". In: *AIPCR* (1995).
- [25] Hao Wang. "Road Profiler Performance Evaluation and Accuracy Criteria Analysis". PhD thesis. Virginia Polytechnic Institute and State University, 2006.
- [26] xsens. "An introduction to the beginning of motion capture technology."