# Bike lane quality estimation under variable speed conditions using off-the-shelf motion sensors

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Traditional pavement maintenance programs are focused on the monitoring of motorized roadways. As a result, new monitoring techniques are required for non-motorized lanes. In this study, an investigation into road roughness detection using an off-the-shelf motion sensor has been conducted. Three different experiments were performed to find a surface roughness estimation technique independent of speed conditions. We selected distinct road surface types to determine how surface materials affect road quality. The results illustrated that when using the IRI standard formula, the roughness of roads decreases as speed increases. To reduce these impacts, a new method was proposed, which proved suitable for surface roughness estimation under variable speed conditions. After testing the system on roads with visible anomalies, we created thresholds of good road quality. All roughness values captured below 0.77 for asphalt roads and 1.27 for tile segments were considered to be from a good surface quality road. The findings of this study are expected to improve the maintenance of unmotorized paths while making bicycle use more safe, reliable, and comfortable.

Additional Key Words and Phrases: Road pavement; Roughness; Bicycle; Motion sensors; IMU; Vibration; Bicycle lane, Speed

## 1 INTRODUCTION

With a bicycle path network consisting of more than 37,000 km, maintaining and rehabilitating transport infrastructure in the Netherlands has become a prime concern for governing entities [1]. Current road maintenance programs are primarily concerned with the rehabilitation of motorized highways and have elevated economic costs. More frequent and accessible maintenance programs are needed to provide users with a safer and more comfortable riding experience. Indications of unfavourable pavement conditions can sometimes be seen with the naked eye, in the form of pavement fractures, distortion, or disintegration [20]. Techniques such as crowdsensing, which can capture massive amounts of high-quality data at lower costs, could be used to monitor the state of unmotorized lanes in real-time [3]. High road roughness levels affect not only the comfort quality of rides but also the life of vehicles and the safety of those riding. Therefore, the use of alternative monitoring techniques should be investigated.

Road roughness, defined as the surface deviations from actual planar conditions, can be efficiently quantified using surveys or evaluation metrics such as the International Roughness Index (IRI) or the Present Serviceability Rating (PSR). They have been designed to be evaluated by certified inspectors using professional instruments like high-speed inertial profilers, dipsticks, and response-type tools. Many are mounted on motorised vehicles, making them inoperable on non-motorised roads [21].

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The IRI is the most well-known and widely used indicator of road surface roughness. It is based on the quarter-car model and constitutes the way a single car tire is affected by the pavement profile. As illustrated in equation 1, it is represented as the sum of the vertical displacement of all sampling intervals divided by the travel distance, where $S$ represents the travelled distance and $\alpha$ the vertical displacement [21].

$$IRI = \frac{\int \int_{tstart}^{tstop} |\alpha_z| \, (dt)^2}{S} \tag{1}$$

Nowadays, smartphones can estimate the roughness of roads. The vertical displacement needed to calculate the IRI may be determined using the smartphone's built-in tri-axial accelerometer. Similarly, a Global Navigation Satellite System (GNSS) module may estimate the total travel distance. As a consequence, when compared to professional measuring equipment, smartphones have the potential to provide promising findings.

Current road monitoring techniques have been designed to be used on motorised roads. Currently, no standard index to evaluate the quality of bicycle lanes has been identified. Alternative methods are therefore needed to deliver safer riding experiences.

In this paper, we will investigate possible correlations between the vibration of bicycles and the roughness of bicycle-lane paths. To improve the maintenance of these roads, we will create a dynamic bicycle roughness index for unmotorised lanes. The paper has been structured in nine different sections: Section 3 presents the related work, Section 4 the research background, and Section 5 highlights the methodology. In Section 6, the different experiments conducted will be explained, of which the results can be found in Section 7. Finally, in Section 8 and 9 respectively, the discussions, conclusions and future work can be found.

## 2 PROBLEM STATEMENT

Although research has been done on alternative road roughness estimation techniques, most of it has focused on motorised roads. Enabling the assessment of unmotorised lanes through bicycles can lower road maintenance costs and provide more frequent feedback to local authorities.

Previous research studies have identified smartphone use inside motorised vehicles as a tool whose collected measures exhibit relationships with standard IRI values [16]. Fewer studies, however, have established a correlation when capturing vibration data on unmotorised conveyances. The smartphone's orientation when capturing this data and outside noise worsens the prediction of bicycle-lane roughness. Moreover, external factors that influence the acquired sensor data are frequently overlooked. Theoretically, cycling speed, tire pressure and damping, sensor placement, and mass of the cyclist and bicycle may all be factors that impact roughness indices [11, 18]. Previous works in the field assume the parameters mentioned above to be stable, as they merely attempt to show a correlation between measurements from professional equipment and their proposed methods. However, these factors should be considered when measuring roughness in a crowdsensing way (from multiple users and devices).

Bicycle lanes consequently require different sensing procedures. The use of off-the-shelf motion sensors as an alternative to using smartphones for data collection can be proven to be a more reliable substitute for road monitoring.

### 2.1 Research Question

To accomplish the goals set in the problem statement; investigate how bicycle-lane surface quality can be estimated under adaptable conditions using off-the-shelf motion sensors, a research question has been constructed, that will be the basis of this research work:

*How can the surface quality of a bicycle lane be assessed using off-the-shelf motion sensors under variable speed conditions?*

To answer this main research question, the following sub-questions have been constructed:

(1) How could off-the-shelf motion sensors be configured and located on a bicycle?
(2) How can the roughness of a bicycle lane be estimated using motion sensors?
(3) How can road surface roughness be calculated independent of cycling speed?

## 3 RELATED WORK

In this section, we will analyze papers on road maintenance and monitoring. Firstly, we will focus on reports documented on anomaly detection using smartphones [1, 7, 8, 14]. Following this, the usage of different roughness indexes will be reviewed. Previous work can help us understand how smartphones can reliably estimate the quality of motorized lanes [2, 16, 21]. Finally, papers focusing on road roughness estimation on unmotorized vehicles will be examined [3, 19, 21].

Road quality assessment and monitoring is a widely studied topic by researchers, with a strong focus on developing alternative maintenance programs. In literature, many papers can be found on the use of smartphones to detect individual road anomalies and pavement distress [1, 7, 8, 14]. These studies revealed that the triaxial accelerometer and Global Positioning System (GPS) are the most often used smartphone sensors for pavement evaluation and, therefore, ideal for use. Together, they allow for the detection and triangulation of pavement anomalies. Additionally, these papers revealed ways to eliminate noise from the collected measurements through filtering techniques. Anomalies can appear for various reasons, and even if a road has been paved recently, this does not indicate a lack of abnormalities. Therefore, by identifying them in real-time, bicycle accidents can be prevented. At the time when this research was conducted, no standard roughness index for bicycle lanes could be found.

Several studies have been conducted on determining road highway roughness through smartphone sensors. The International Road Roughness Index (IRI) was the most studied parameter [16], although there are other road roughness indexes available like the Present Serviceability Rating (PSR) or the Pavement Quality Index (PQI). Further, there have been a few studies that focus on the use of quality management standards like ISO to determine ride comfort and consequently identify road quality conditions [2, 6]. These studies revealed that under the right circumstances, there exists a correlation between bicycle vibration data and the roughness/quality of the roads.

Although in literature many research papers deal with the use of smartphone sensors to determine road conditions on motorized vehicles, few studies try to determine roughness of roads through the use of non-motorized transportation modes [3, 11]. These two studies revealed that the sensors used to assess road anomalies can also be utilized to measure road quality.

In the paper [21], the authors proposed a method for evaluating road roughness on un-motorable roads. To do that, they collected accelerometer data on a bicycle-mounted smartphone at stable speeds. Through their experiments, the authors were able to show a correlation between the road roughness values captured by their proposed method and those from professional measuring equipment. Nevertheless, it was suggested that the effects of different riding styles, cycling speeds, bicycle models, and smartphone installation positions should be considered for accurate roughness estimation.

In [18], O.Wage studied the roughness of bike lanes. To do that, he developed a phone application that captured vertical accelerometer data. From it, the IRI, the standard deviation (STD), and the Dynamic Comfort Index (DCI) index were calculated in different test setups. With his experiments, the author proved that road vibrations are also affected by external factors like speed and tire pressure. Nonetheless, no method was proposed to reduce the impact of these external factors.

The application of Artificial Intelligence (AI) tools for traffic monitoring, particularly machine learning approaches based on image recognition, has grown in recent years. The authors of [12] advocated using a linear discriminant analysis to classify different road types (asphalt, pebble, and bumpy paths). Their findings revealed that their proposed strategy was more than 90% accurate. In [4], a machine learning algorithm was developed, capable of detecting road abnormalities like speed bumps with an accuracy of 97%. The implementation of algorithms such as Neural Networks (NN) or Support Vector Machines (SVM) on accelerometer data has been investigated in a few instances.

To summarize, the use of smartphone sensors to estimate road roughness has been widely studied and validated for motorized vehicles. Still, little research has been conducted on determining a dynamic index for bicycles using motion sensors. Even though it has been proven that road roughness can be estimated under stable conditions using smartphones, it is not yet known how the effects of these conditions could be reduced. Based on findings, a research study is needed to investigate alternative non-motorized road maintenance programs that do not rely on smartphone orientation and are not affected by external factors like travel speed.

## 4 BACKGROUND

This section will highlight the importance of evaluating roads with different surface types differently. Additionally, to understand how surface quality can be assessed, we will describe the road monitoring methods used by different regions of the Netherlands.

As mentioned in the introduction, this work aims to discover an alternate technique of road infrastructure monitoring. The proposed method should be more affordable, scalable, and capable of assessing non-motorized paths. To speed up the current road monitoring process, a method for determining when roads need to be repaired must be developed. Previous research studies have focused on estimating the roughness of paths without creating thresholds for different road surface types. However, when the road surface type is unclear, it is not possible to determine whether road repairs are required. A high roughness index does not always indicate that a road's condition is poor or that it needs to be fixed. For example, a well-paved tile path with no anomalies will have greater vertical acceleration values than a smooth asphalt road, as illustrated in Figure 1. Similarly, a poorly paved asphalt path might have the same vertical acceleration values as a well-paved tile path. Therefore, knowing the surface type is required for surface roughness estimation.

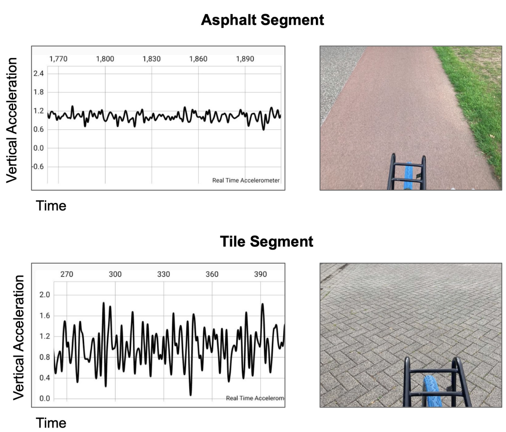


Fig. 1. Vibrations in asphalt and tile roads

To evaluate whether repairs on a specific path are required, thresholds per road surface type; upper and lower roughness limits, must be established. As previously stated, to design the thresholds, we must first determine the path we are on. This research paper will assume that the road type is known. The threshold may then be calculated based on the steady accelerometer measurements collected while cycling under ideal conditions. We will investigate a mechanism for proposing alternative thresholds further in Section 6.

Before implementing new road monitoring systems, it is crucial to identify how cities and regions are currently monitoring their roads. For this thesis, the municipality of Enschede, a region of the Netherlands, was contacted. They are now employing a procedure known as visual inspection weighing from the CROW norm, a publication available for governing entities. The most significant disadvantage of this system is that it is manual, and only certified inspectors can monitor the roadways. Passing a theory exam as well as a practice are required for certification [5]. To emphasize the significance of the problem addressed by this thesis work, it is vital to mention the municipality's enthusiasm and willingness to test the final product to be developed.

In summary, roughness thresholds need to be created per surface type to determine whether repairs on a particular road segment are required. Furthermore, after contacting the municipality of Enschede, their need for a new road monitoring system was proven.

## 5 METHODOLOGY

In this section, the methodological approach performed to conduct this research study will be explained.

To comprehensively address the research question stated in Section 2; evaluate how the surface quality of a bicycle lane may be assessed using motion sensors under variable speed conditions, the following approach was implemented. First, a literature review was undertaken to establish the hardware needed for road roughness assessment. Possible sensor placement locations were also investigated. Second, research publications were examined to assess how data from the chosen sensor could be acquired. The sensor data was then collected, pre-processed, and analyzed to investigate how different factors influence the vibration of roads. Two strategies were selected and implemented to test the feasibility of creating thresholds for various surface types; the highest and lowest vertical acceleration values and the IRI method. More details on the data collection, processing, and acquisition process can be found on the flowchart illustrated in Figure 2. Finally, the results were studied, and a strategy for minimizing the impacts of speed conditions when measuring road roughness was proposed.

### 5.1 Sensor placement and configuration

As stated in the introduction, bicycles with integrated sensors could generate new opportunities in the automobile industry. Through crowdsensing tools; where many devices collectively share data and extract information, user experience and safety while cycling can be increased. This section will describe the hardware selected for this project, the ideal sensor placement, and its configuration.

Crowdsensing tools can allow for real-time road quality monitoring. Nevertheless, they have some limitations. One of the biggest bottlenecks of crowdsensing instruments is that they are energy-constrained [13]. When using Bluetooth to communicate with other devices, battery consumption levels increase. On the contrary, when using Bluetooth Low Energy (BLE); a wireless personal area network that runs independently of classic Bluetooth, devices can run powered by batteries for more extended periods. The reason is that

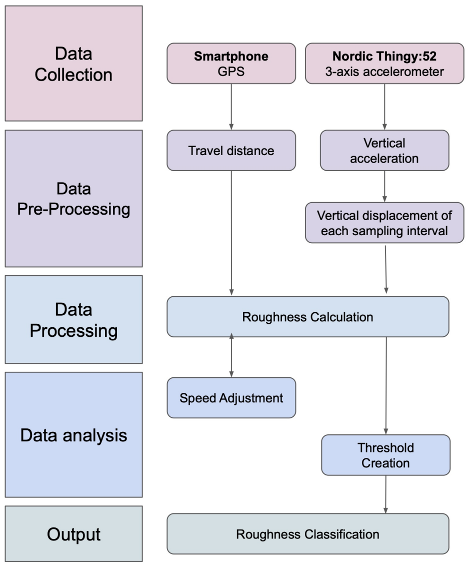


Fig. 2. Flowchart: Data collection, pre-processing and analysis

BLE devices are constantly in sleep mode, except when a connection is initiated [13]. Therefore, BLE devices can be preferred for road monitoring systems.

Out of all the BLE devices with built-in accelerometers available in the market, the Nordic Thingy:52 has been the one chosen for this project. It is compact, counts with a rechargeable 1440 mAh battery, and allows data collection from multiple sensors (environmental, motion, sound, etc.). The multi-sensor functionality might allow for the development of alternative sensing platforms, capable of improving the connected vehicles ecosystem of the future. To connect this sensor with a smartphone, a bridge has to be built. This can be done by developing a BLE scanner on a smartphone application that allows users to connect to a BLE device. Once connected, the sensor can be configured using the 'thingylib' library [1].

In research, the most common sensor placements in bicycles are in the handlebar and the seat [15]. These locations are contact points between the cyclists and the bike, which can be used to measure ride comfort estimation. Nevertheless, this research paper aims to measure bike-lane surface quality by detecting the input vibrations from the road surface. By placing the sensors in any of the above-mentioned arrangements, the data captured would experience a higher degree of influence by human reflexes and bicycle suspension systems. And with the front and rear wheels being the closest points to the ground in a bicycle, selecting them as ideal locations to measure the input vibrations from the road surface is reasonable. A summary of the chosen sensor configuration can be found in Table 1. Additionally, Figure 3 illustrates the final placement of the sensor, which was firmly attached with tape to the bicycle.

[1]Thingy Library for Android

Table 1. Sensor Configuration

| | |
|---|---|
| Communication medium | BLE (streaming to a smartphone) |
| Device name | Nordic Thingy:52 |
| Sensing parameters | x,y,z axis acceleration |
| Sampling rate | ~ 10 Hz |
| Positioning | Front wheel |

This section highlighted why BLE devices are preferred for surface quality estimation due to their extended battery lives. In particular, we selected the Nordic Thingy:52 sensor for this study for its multi-sensing capabilities. To configure the sensor, the 'thingylib' library was utilized. To prevent the influence that riders and suspension systems may have on the acquired data, and due to its closeness to the ground, the front wheel location was chosen for sensor positioning.


Fig. 3. Installation of the Nordic Thingy:52

## 5.2 Roughness Calculation

This section describes how surface roughness can be estimated using off-the-shelf sensors. As a starting point, two strategies were chosen for roughness estimation: the highest/lowest vertical acceleration values and the IRI standard formula. To the writer's knowledge, the first strategy selected has not yet been used in research. On the contrary, the IRI is a widely used method for roughness estimation. The results obtained from these two techniques will show whether we can use them to estimate surface roughness using off-the-shelf motion sensors. To determine if they can assess roads' quality, the measurements must show a clear difference between good and poor surface quality conditions.

*5.2.1 Vertical acceleration.* When cycling, road surface flaws cause bicycles to experience minor vertical leaps and falls, commonly referred to as vertical accelerations. If the highest and lowest vertical acceleration values experienced on a particular surface type are known, it might be possible to estimate the quality of a road. To obtain the vertical acceleration value from the Nordic Thingy:52 sensor, which is more precise than a smartphone's built-in accelerometer, its tri-axis accelerometer may be used. The z-axis cannot be directly taken as the final vertical acceleration value due to the tilting motion that bicycles experience during turns. Therefore, data pre-processing is needed. All accelerometer dimensions need to be considered for computing the vertical acceleration value while excluding the influence of tilting. The final gravitational vertical acceleration value can be calculated following Formula 2 proposed by K.Zang, where $A_x$, $A_y$ and $A_z$ represent any acceleration output at their respective axis, and $\bar{A_x}$, $\bar{A_y}$, and $\bar{A_z}$ the average acceleration after calibration [21].

$$A_v = A_x * \bar{A_x} + A_y * \bar{A_y} + A_z * \bar{A_z} \tag{2}$$

To calculate $\bar{A_x}$, $\bar{A_y}$, and $\bar{A_z}$, users are required to keep the bicycle in a static stand position for five seconds before the acquisition process. This is needed for positioning calibration, in order to create a reference vector $\bar{A_v} = (\bar{A_x}, \bar{A_y}, \bar{A_z})$.

The average highest and lowest vertical acceleration points can be derived from the outputs of the gravitational vertical acceleration data $A_v$. They can be computed by determining every high and low peak in the sensor wave at a time interval and saving them in two separate arrays. At the end of each sampling interval, the average of the returned two array values can be computed, resulting in the average of the highest and lowest vertical acceleration values. With them, a threshold of good riding conditions can be obtained. Any road path segment with average accelerometer values outside the higher and lower limit can be considered to have poor road conditions (rough path).

*5.2.2 International Roughness Index.* The International Roughness Index is one of the most widely used roughness indices. Even though it was designed to be used with sensor measurements from motorized vehicles, previous studies have tried to use it for bike-lane roughness estimation. As illustrated in Formula 1, it can be calculated using the vertical acceleration value and the trip duration. To facilitate its computation, the formula can be adjusted. The numerator of the IRI standard formula is equal to the sum of the vertical displacement in a sampling time interval, where $h$ is the longitudinal offset of a road surface. The term vertical displacement refers to the distance moved in the vertical direction from one point to another. Therefore, the current vertical displacement is equal to the longitudinal offset $h$ at time $i$ minus the offset at time $i-1$, where the longitudinal offset is the height of a wave from the reference axis. The final vertical displacement can then be calculated using Formula 3 [21].

$$\int \int_{tstart}^{tstop} |\alpha_z| \, (dt)^2 = \sum_{i=2}^{n} |h_i - h_{i-1}| \tag{3}$$

Finally, the speed gathered at each sampling point; which can be obtained directly from the smartphone's GPS module, may be used to compute the total travel distance $S$. Even though it is obtained from a smartphone, the speed has a reported accuracy ranging from 0.1 m/s to 0.2 m/s. By using Formula 4, where $V$ is the measured travel speed at time $t$, the total travel distance can be computed [21]. With these parameters; travel distance and the sum of vertical displacements in a sampling period, the IRI value can be calculated following Formula 1.

$$S = \int_t^0 V_t dt \tag{4}$$

To summarize, two strategies for estimating surface roughness have been presented in this section. The highest and lowest vertical acceleration approach assesses road roughness by constructing higher and lower vertical acceleration limits. Any value exceeding the limit is considered part of a poor road section. On the other hand, the IRI approach uses the sum of vertical displacements in a sampling interval divided by the total travel distance to assess the roughness of a path. In Section 7, we will analyze the efficacy of both techniques.

## 6 EXPERIMENTS

This section will describe the three experiments conducted to answer the questions proposed in Section 2. The first experiment attempts to determine a strategy for roughness estimation under different surface types using two techniques. The second experiment seeks to determine the roughness of roads independent of different cycling speeds. Finally, the third experiment tries to establish an appropriate threshold of good surface conditions.

To obtain and process the sensor data, we developed a smartphone application. In all three experiments, we used this application. The application interface had the following components: a graph to display the gathered accelerometer data, a button to start and stop the data recording, a text view showing the current driving speed, a text field to insert the desired segment length and a map view. After collecting and preprocessing data for each road segment, the system placed a marker on the map view with the gathered information. You can observe more details about the test setup in Table 2.

Table 2. Test setup

| | |
|---|---|
| Bicycle brand | Swapfiets |
| Bicycle model | Original |
| Bicycle weight | 15kg |
| Tire width | 47 mm |
| Segment length | 20 m |
| Surface type | Asphalt and tiles |

### 6.1 Experiment 1 - Roughness calculation

A controlled experiment was conducted to evaluate how a bicycle lane's surface roughness may be estimated using motion sensors. We identified roads with tile and asphalt surface types with no visible anomalies and selected 20-meter sections. The experiment was conducted at constant speeds ranging from 10 to 25 km/h. Additionally, we computed the average highest and lowest vertical acceleration values and the standard IRI values during each run. For this experiment, three segments of each road surface type were run (60-meter sections). The IRI was the method selected for road roughness estimation based on the results, which we will further discuss in the next section.

### 6.2 Experiment 2 - Speed correction

This section investigates how different cycling speeds affect the IRI formula and presents a method for evaluating surface roughness independent of velocity. We used the same test setup as for experiment 1 for this experiment. Different runs were performed at the selected 20 meter segments, with constant speeds ranging from 10-15 km/h (slow), 15-20 km/h (medium), and 20–25 km/h (fast). For each surface type, twenty-one runs were completed (seven per cycling speed). During each run, the IRI value was calculated.

We believe that speed will impact road roughness based on the findings of O.Wage [18]. When estimating roughness in a crowd-sensing manner, the effects of different speeds should be minimized to effectively classify the condition of road segments based on their true roughness condition. Users should obtain the same roughness value regardless of travel speed when travelling on fixed road sections. A first test was conducted to prove our hypothesis. The results, which can be observed in Section 7, confirmed that our reasonings were correct; speed influences road roughness. Based on the results, a second test was performed to minimize the impacts of that influence.

### 6.3 Experiment 3 - Roughness threshold

Knowing a road's roughness value is only beneficial if we understand what that value entails. As a result, thresholds must be created to determine whether road repairs are required. In this experiment, we will attempt to find the roughness limits for several surface types. We selected additional segments with ideal conditions to demonstrate that the same roughness values can be obtained from asphalt and tile segments other than those used in experiments 1 and 2. Furthermore, we identified segments with visible anomalies to analyze if the roughness values under poor road conditions fall outside the determined thresholds of good surface quality.

To summarise, we identified six segments with no visible anomalies for this experiment, and three different runs were performed on each. In addition, runs in six other segments with visible anomalies were also conducted. In Section 7, the findings of these two tests can be found.

## 7 RESULTS

This section will describe and discuss the results of the three different experiments performed. The findings will determine if we can use the proposed roughness estimation method to measure road surface quality under variable speed conditions.

### 7.1 Experiment 1

This first experiment aimed to find a way to estimate the roughness of a bicycle lane using motion sensors. We used two techniques to compute the roads' roughness: the highest and lowest vertical acceleration values and the IRI. The results from the test runs can be observed in Table 3 and 4.

As illustrated, the highest vertical accelerometer value captured during the three trials was 1,34 on an asphalt segment and 1,42 on the tiled one. In addition, the lowest acceleration values recorded were 0.82 and 0.67, respectively. This places the suitable riding condition threshold of vertical accelerometer values between (0.82, 1.34) for asphalt roads and (0.67, 1.42) for tile paths. Therefore, when using this method, the threshold for asphalt roads is located inside the threshold for tiled roads, leading to no clear division between different road segments.

Table 3. Highest and lowest vertical acceleration values

| | Highest $A_v$ | | Lowest $A_v$ | |
|---|---|---|---|---|
| | Asphalt | Tiles | Asphalt | Tiles |
| Trial 1 | 1,15 | 1,24 | 0,94 | 0,77 |
| Trial 2 | 1,34 | 1,42 | 0,88 | 0,67 |
| Trial 3 | 1,15 | 1,23 | 0,82 | 0,75 |

Table 4. IRI roughness value

| | IRI | |
|---|---|---|
| | Asphalt | Tiles |
| Trial 1 | 0,49 | 0,95 |
| Trial 2 | 0,42 | 0,75 |
| Trial 3 | 0,46 | 0,86 |

On the contrary, when using the IRI method, clear divisions can be observed between asphalt and tiled paths. Based on the results, the threshold of good riding conditions under the IRI technique would be (0.42, 0.49) for asphalt segments and (0.75, 0.95) for tiled paths.

In conclusion, the results of this experiment have shown that the IRI technique is a suitable method for surface roughness estimation using motion sensors. On the other hand, the vertical acceleration method does not enable the creation of thresholds per surface type. Therefore, it has been considered unsuitable for assessing the quality of roads.

### 7.2 Experiment 2

This second experiment aimed to determine a roughness formula that was not reliant on velocity. To do that, two different tests had to be performed. In the first test, we identified the impacts of velocity on roughness estimation. With them, a new roughness formula was proposed. The second test attempted to demonstrate the efficacy of the suggested speed correction algorithm.

The results of the first test, illustrated in Table 5, revealed that, in line with our hypothesis, greater speeds resulted in lower roughness levels. Overall, the roughness difference between slow and fast speeds was 0.06 on asphalt paths. On the other hand, this difference was only 0.21 on tile segments. This result also shows that the effects of speeds increase as the road conditions worsen. Due to the lack of surface defects on paved segments, the influence caused by different speed conditions was relatively small. As a result, it can be observed that the gap between slow and fast speeds widens as road conditions deteriorate.

To decrease the impacts of different cycling speeds, we added a constant to the numerator component of the IRI standard formula.

Table 5. Road roughness before speed correction

| | Average IRI value | |
|---|---|---|
| Speed | Asphalt | Tiles |
| Slow (10-15 km/h) | 0,49 | 0,98 |
| Medium (15-20 km/h) | 0,45 | 0,81 |
| Fast (20-25 km/h) | 0,43 | 0,77 |

Adding a constant to the denominator of the formula would only increase the effects of different driving speeds. Because speed was the only variable that was not kept constant throughout the experiment, it was multiplied by the constant to consider the difference between distinct cycling speeds. To obtain this variable, we modified the IRI formula with an unknown variable $c$, where $R$ is the roughness of road type $r$; $h_i$ is the longitudinal offset of a road surface, and $v$ is the velocity at an average speed of $s$:

$$R_r = \frac{\sum_{i=2}^{n} |h_i - h_{i-1}| + c * v_s}{S}$$

We solved the equation for $c$ such that the roughness value of a tile segment $R_t$ for different speeds remains the same.

$$R_{ts} = R_{tm}$$
$$\frac{\sum_{i=2}^{n} |h_i - h_{i-1}| + c * v_s}{S} = \frac{\sum_{i=2}^{n} |h_i - h_{i-1}| + c * v_m}{S}$$
$$\frac{19,6 + c * 12,5}{20} = \frac{16,1 + c * 17,5}{20}$$
$$c = 0,148$$

$$R_{tm} = R_{tf}$$
$$\frac{\sum_{i=2}^{n} |h_i - h_{i-1}| + c * v_m}{S} = \frac{\sum_{i=2}^{n} |h_i - h_{i-1}| + c * v_f}{S}$$
$$\frac{16,1 + c * 17,5}{20} = \frac{15,36 + c * 22,5}{20}$$
$$c = 0,7$$

The results showed that to minimise the effects of different driving speeds, a constant variable between 0,148 and 0,7 could be used. Through trial-and-error, 0,35 was the constant selected. Formula 6 displays our proposed speed correction method.

$$R = \frac{\sum_{i=2}^{n} |h_i - h_{i-1}| + 0,35 * ((\sum_{i=0}^{N} v_i)/N)}{S} \tag{5}$$

With this new formula, an additional test was performed. We kept the test setup constant and conducted twenty-one additional test runs. The results of the experiment can be found in Table 6.

Table 6. Road roughness after speed correction

| Speed | Average R | | Highest R | | Lowest R | |
|---|---|---|---|---|---|---|
| | Asphalt | Tiles | Asphalt | Tiles | Asphalt | Tiles |
| Slow | 0,58 | 0,99 | 0,66 | 1,27 | 0,46 | 0,81 |
| Average | 0,58 | 0,95 | 0,77 | 1,03 | 0,48 | 0,83 |
| Fast | 0,59 | 0,98 | 0,63 | 1,20 | 0,56 | 0,79 |

As illustrated, the proposed speed correction formula has proven to be a success. The roughness value disparity between slow and fast travel speeds has decreased significantly. In tile paths, it went from being 0.21 before speed correction to 0.04 afterwards. Similarly, the roughness value difference in asphalt routes was 0.06 before and 0.01 after that. Based on the results, we can create a threshold of good riding conditions from the average of the highest and lowest roughness values. This threshold goes between (0.77,0.46) for asphalt paths and (1.27, 0.79) for tiled segments.

On the whole, the results of this experiment have demonstrated that when calculating road roughness using the IRI method, the results are affected by different cycling speeds. Road roughness values decrease as speed increases. A speed correction method was proposed to minimise these impacts, which proved to be successful. More testing should be performed to confirm that this initial threshold can be used for alternative road segments.

## 7.3 Experiment 3

This third experiment aimed to obtain a threshold of good road conditions per surface type. Two different tests were required to obtain this. The first one, whose results can be observed in Table 7, attempted to demonstrate that the findings from Experiment 2 are equivalent for different road segments. As illustrated, the roughness values captured on the new road segments selected are very similar to those obtained in Experiment 2. The average roughness value for asphalt segments decreased from 0,58 to 0,48. The reason for this is that the asphalt path selected had been paved recently. Moreover, the average roughness value on tile segments was 0,93, when previously it had been around 0,97. Even though we picked different paths, the difference between the obtained roughness values was minimal. Therefore, we can conclude that regardless of the street segment, if a road has good roughness conditions, its roughness values will be below 0,77 for asphalt paths and below 1.27 for tile segments.

Table 7. Alternative segments with ideal conditions

| | Average R | Highest R | Lowest R |
|---|---|---|---|
| Asphalt | 0,48 | 0,53 | 0,44 |
| Tiles | 0,93 | 1,15 | 0,84 |

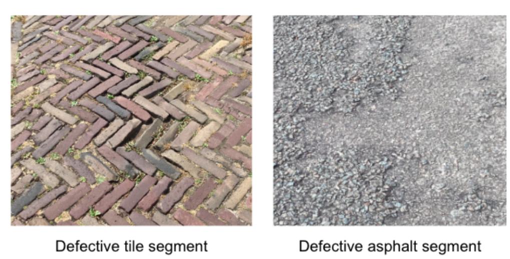


Fig. 4. Defective road segments

The second test was performed on roads with visible poor quality, illustrated in Image 4. You can find the results of this test in Table 8.

As it can be observed, the tile segment's average roughness value was 1,75. In addition, the average roughness value of the asphalt sections with visible anomalies was 0,95. It is worth noting that there aren't many anomalous asphalt sections in the region where the experiments were performed. As a result, the lowest roughness value in one of the segments was 0,70, within the acceptable quality threshold determined in the above paragraph. Therefore, even though the experiment was performed on asphalt roads considered to have lower quality, we can conclude that the condition of these segments was not that deficient.

Table 8. Bad quality road segments

| | Average R | Highest R | Lowest R |
|---|---|---|---|
| Asphalt | 0,95 | 1,33 | 0,70 |
| Tiles | 1,75 | 2,2 | 1,39 |

Based on these findings, we can conclude that roads with values above 0,77 would be categorised as bad road conditions for asphalt sections and above 1,27 for tile segments. Table 9 illustrates the final threshold of good riding conditions, calculated under the speed correction formula.

Table 9. Roughness Threshold

| | Threshold of good road quality |
|---|---|
| Asphalt | < 0,77 |
| Tiles | < 1,27 |

In this section, three different experiments were conducted. Their results established a relationship between cycling speeds and road roughness values. They illustrated that the IRI could be a suitable roughness estimation method if the impacts of different velocities were reduced. After proposing a new roughness estimation technique, we obtained consistent measurements independent of speed. With the results, a threshold of good surface quality for different surface types was proposed, with upper limits of 1.27 for tile paths and 0.77 for asphalt segments. Due to time constraints, we did not evaluate the proposed method. By comparing the results to those from the municipality of Enschede dataset, we could obtain a quantitative evaluation. Similarly, we could conduct a qualitative assessment with feedback from road maintenance inspectors. With these evaluations, we expect the experiment results to improve while facilitating the monitoring and maintenance of roads in the region.

## 8 DISCUSSION

This section will explain and evaluate our findings. As illustrated in Section 7, the paper proved that the quality of non-motorised roads can be analysed while cycling through an off-the-shelf motion sensor. In Section 7.1, the IRI method was proved capable of assessing the quality of roads. In line with the hypothesis, Section 7.2 revealed that travel speeds influenced the roughness values calculated using this method. Nevertheless, the results of paper [11] showed that contrary to our findings, higher velocities led to higher roughness values. Therefore, the influence of the factors kept stable in our experiments (bicycle weight, tire pressure, tire width, suspension systems, etc.) should be studied further to analyse its impact. In addition, in Section 7.3 a threshold of good road conditions was constructed, which can be observed in Table 9. Due to time constraints, we did not compare the system's performance to other roughness estimation techniques. However, we believe that a quantitative or qualitative evaluation will help to improve our findings.

## 9 CONCLUSIONS AND FUTURE WORK

Maintaining and rehabilitating transport infrastructure has become a prime concern for governing entities. Currently, most road monitoring techniques are time-consuming and have been designed to be utilized on motorized roads. With the extensive bicycle infrastructure available in the Netherlands, alternative monitoring techniques are required. Until now, most research studies that have attempted to build a roughness index applicable to bicycles using smartphones. However, factors like phone orientation are a constrain in a crowd-sensing setting. This research paper tried to find a way to estimate the surface quality of bicycle lanes using off-the-shelf motion sensors under variable speed conditions. Three experiments were conducted; roughness calculation, speed correction and roughness threshold creation.

The Nordic Thingy:52 sensor was selected and placed on the bicycle's front wheel to determine road quality. This sensor not only has a BLE communication mechanism, enabling it to have a longer battery life, but also a multi-sensor capability. The experiments' results proved that our hypothesis was correct; speed influences the International Roughness Index. Our proposed speed correction method, designed to minimize these effects, obtained consistent roughness measurements at different velocities. Therefore, we might use this approach to determine road quality under variable speed conditions. From the results, we created a threshold of good surface conditions. All roughness values below 0.77 for asphalt paths and 1.27 for tile segments are considered to be part of a good road segment.

In conclusion, this research paper has proven that the use of onboard motion sensors is suitable for evaluating the quality of roads under variable speed conditions. The findings bring us closer to the possibility of an intelligent bicycle ecosystem in the future, where bicycle use could become more reliable, safer and comfortable. In the subsequent research phases, we will evaluate the system and investigate the influence of external factors like tire width and pressure.

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## REFERENCES


[1] Azza Allouch, Anis Koubaa, Tarek Abbes, and Adel Ammar. 2017. RoadSense: Smartphone Application to Estimate Road Conditions Using Accelerometer and Gyroscope. *IEEE Sensors Journal* 17, 13 (7 2017), 4231–4238. https://doi.org/10.1109/JSEN.2017.2702739

[2] Adam Azzoug and Sakdirat Kaewunruen. 2017. RideComfort: A Development of Crowdsourcing Smartphones in Measuring Train Ride Quality. *Frontiers in Built Environment* 3 (2 2017). https://doi.org/10.3389/fbuil.2017.00003

[3] Salvatore Cafiso, Alessandro Di Graziano, Valeria Marchetta, and Giuseppina Pappalardo. 2022. Urban road pavements monitoring and assessment using bike and e-scooter as probe vehicles. *Case Studies in Construction Materials* 16 (6 2022), e00889. https://doi.org/10.1016/j.cscm.2022.e00889

[4] Jose Celaya-Padilla, Carlos Galván-Tejada, F. López-Monteagudo, O. Alonso-González, Arturo Moreno-Báez, Antonio Martínez-Torteya, Jorge Galván-Tejada, Jose Arceo-Olague, Huizilopoztli Luna-García, and Hamurabi Gamboa-Rosales. 2018. Speed Bump Detection Using Accelerometric Features: A Genetic Algorithm Approach. *Sensors* 18, 2 (2 2018), 443. https://doi.org/10.3390/s18020443

[5] ’ ’CROW. 2013. Inspectiekaart globale inspectie. https://www.crow.nl/getmedia/bcfb23b9-8d75-46e1-84a7-5760b251da37/P146b-Inspectiekaart-globale-inspectie-versie-febr-2013.aspx

[6] Hongyang Zhao, Huan Zhou, Canfeng Chen, and Jiming Chen. 2013. Join driving: A smart phone-based driving behavior evaluation system. In *2013 IEEE Global Communications Conference (GLOBECOM)*. IEEE, 48–53. https://doi.org/10.1109/GLOCOM.2013.6831046

[7] Moez Krichen. 2021. Anomalies Detection Through Smartphone Sensors: A Review. *IEEE Sensors Journal* 21, 6 (3 2021), 7207–7217. https://doi.org/10.1109/JSEN.2021.3051931

[8] Senthan Mathavan, Khurram Kamal, and Mujib Rahman. 2015. A Review of Three-Dimensional Imaging Technologies for Pavement Distress Detection and Measurements. *IEEE Transactions on Intelligent Transportation Systems* 16, 5 (10 2015), 2353–2362. https://doi.org/10.1109/TITS.2015.2428655

[9] n.d. 2022. Cycling holiday in Holland. https://www.holland.com/global/tourism/activities/cycling.htm

[10] n.d. 2022. Nordic SemiConductor. https://www.nordicsemi.com/

[11] Mark Olieman, Raluca Marin-Perianu, and Mihai Marin-Perianu. 2012. Measurement of dynamic comfort in cycling using wireless acceleration sensors. *Procedia Engineering* 34 (2012), 568–573. https://doi.org/10.1016/j.proeng.2012.04.097

[12] Daiyan Peng, Zach Strout, Shuo Jiang, and Peter Shull. 2019. A Road Condition Classifier via Lock Embedded IMU on Dock-Less Shared Bikes. In *Proceedings of the International Conference on Industrial Control Network and System Engineering Research - ICNSER2019*. ACM Press, New York, New York, USA, 32–36. https://doi.org/10.1145/3333581.3333597

[13] Arpita Ray, Sakil Mallick, Sukanta Mondal, Soumik Paul, Chandreyee Chowdhury, and Sarbani Roy. 2018. A Framework for Mobile Crowd Sensing and Computing based Systems. In *2018 IEEE International Conference on Advanced Networks and Telecommunications Systems (ANTS)*. IEEE, 1–6. https://doi.org/10.1109/ANTS.2018.8710083

[14] Shahram Sattar, Songnian Li, and Michael Chapman. 2018. Road Surface Monitoring Using Smartphone Sensors: A Review. *Sensors* 18, 11 (11 2018), 3845. https://doi.org/10.3390/s18113845

[15] Matthias Springer and Christoph Ament. 2020. A Mobile and Modular Low-Cost Sensor System for Road Surface Recognition Using a Bicycle. In *2020 IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems (MFI)*. IEEE, 360–366. https://doi.org/10.1109/MFI49285.2020.9235233

[16] Ram Thilak, Anjaneyappa, Jeet Mehta, Vivikt Pharle, Chaturi Rajapur, and Sabina Borah. 2021. Evaluation of Pavement Roughness Using Smartphones. In *2021 IEEE International Conference on Computation System and Information Technology for Sustainable Solutions (CSITSS)*. IEEE, 1–7. https://doi.org/10.1109/CSITSS54238.2021.9682804

[17] Joachim Vanwalleghem, Ives De Baere, Mia Loccufier, and Wim Van Paepegem. 2013. Sensor design for outdoor racing bicycle field testing for human vibration comfort evaluation. *Measurement Science and Technology* 24, 9 (9 2013), 095002. https://doi.org/10.1088/0957-0233/24/9/095002

[18] O. Wage, U. Feuerhake, C. Koetsier, A. Ponick, N. Schild, T. Beening, and S. Dare. 2020. RIDE VIBRATIONS: TOWARDS COMFORT-BASED BICYCLE NAVIGATION. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* XLIII-B4-2020 (8 2020), 367–373. https://doi.org/10.5194/isprs-archives-XLIII-B4-2020-367-2020

[19] Hideo YAMANAKA and Susumu NAMERIKAWA. 2006. Evaluation method of road roughness profile using IRI index for sidewalks used by bicycles, wheelchairs and pedestrians. *INFRASTRUCTURE PLANNING REVIEW* 23 (2006), 1065–1071. https://doi.org/10.2208/journalip.23.1065

[20] Bill X. Yu and Xinbao Yu. 2006. Vibration-Based System for Pavement Condition Evaluation. In *Applications of Advanced Technology in Transportation*. American Society of Civil Engineers, Reston, VA, 183–189. https://doi.org/10.1061/40799(213)31

[21] Kaiyue Zang, Jie Shen, Haosheng Huang, Mi Wan, and Jiafeng Shi. 2018. Assessing and Mapping of Road Surface Roughness based on GPS and Accelerometer Sensors on Bicycle-Mounted Smartphones. *Sensors* 18, 3 (3 2018), 914. https://doi.org/10.3390/s18030914