19th IMEKO TC10 Conference
"MACRO meets NANO in Measurement for Diagnostics, Optimization and Control"
Delft, The Netherlands, September 21–22, 2023

Development of machine learning assisted suspension vibration data-based road quality classification system

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Abstract **– Vibrations in road vehicles can have highly harmful effects on both the vehicle components and the passengers. These vibrations are mainly caused by low-quality pavement, so it is important to keep the road network in good condition and to know its general quality. In our study, we present the development of a universally applicable, low-cost measurement system for the purpose of measuring the condition of pavement surfaces. The system can be used to identify road sections in urgent and near future need of maintenance, thus helping to schedule construction works efficiently. The system is based on an inertial sensor unit mounted on the vehicle suspension, in contrast to previous systems, and therefore offers an improvement in the accuracy of the measurement. In our study, a principal component analysis and time series segmentation-based algorithm is introduced to extract relevant features from the raw sensor data. Subsequently, each segment is classified into pre-defined classes based on its surface quality using a binary decision tree-based classification model fitted by supervised learning. After validation, the system is tested on public roads under real measurement conditions.**

Keywords – Road quality monitoring, Machine learning, IMU, Software sensor development, Principal component analysis, Decision tree, Road classification.

I. INTRODUCTION

The quality of road surfaces has a major impact on vehicles, passengers, and traffic flows. Poor quality or uneven road surfaces increase the risk of failure of electronic and mechanical components of the vehicle, while vibrations in the human body can cause a short-term negative effects, such as reduction in travel comfort level and long-term damages to health [1][2]. Furthermore, as the degradation of the surface increases, the renovation costs increase at an exponential rate, which is explained by the deterioration curve [3][4]. Uneven road surfaces also affect the dynamics of vehicle movements. Traction conditions are primarily determined by terrain characteristics, with implications for longitudinal and lateral wheel slips [5][6].

Related to the listed reasons, it is essential to keep the road network in good condition and to repair any road defects as soon as possible. There are several methods available to measure road quality [7][8]. The most common method is still based on visual inspection, however the disadvantage of this method is the subjective and uncertain accuracy of monitoring [9][10]. The most accurate solution is offered by specially adapted measuring vehicles with a wide range of sensors, such as LIDAR and camera-based detection. These systems can provide very high accuracy mapping, although their operational costs are high, thus limiting their application [11].

Recently, a significant amount of research has been dedicated to the development of road quality measurement systems based on alternative methods. These usually use one or two sensors for detection, and then data processing is done by various software-sensor solutions. These newer systems can therefore approach or even reach the accuracy of conventional, more expensive systems, making them a good alternative for monitoring lower-grade or less frequented roads [12].

These systems usually use vibration sensors, such as single-axis accelerometers or inertial measurement units (IMU) mounted in the passenger cabin, and in many cases only a smartphone-based data collection was implemented, which allowed a low-cost and simple application [13][14]. In our previous study [15], we developed a data collection system to examine data from the cabin and suspension, which showed that the latter had a higher useful information content. This is due to the damping and spring elements between the suspension and the cabin can significantly modify the frequency and reduce the amplitude of the vibrations that occur [16]. Based on this, by collecting data directly on the suspension, the accuracy of these systems can be increased further, and the depth of the machine learning model can be decreased, allowing faster data processing and less power consumption.

Given the problems described, this work aims to develop and implement a universally applicable, compact and low-cost measurement system with an input from a suspension-mounted IMU sensor. We also investigate the possible causes of measurement errors and thus the possibilities for increasing accuracy, the principles of which will be implemented in the development. Based on data from a multi-axis accelerometer and gyroscope, the device is able to classify road sections of varying lengths, coherent in pavement surface quality into three quality classes using a soft-sensor based architecture.

II. PREVIOUS VIBRATION-BASED PAVEMENT MONITORING METHODS

Several studies have been carried out on pavement damage detection systems based on vibration data. The measurement principle is based on the motions caused by surface irregularities, on which a good estimation of the road surface quality can be obtained [1]. Road defects cause mainly vertical, namely Z-direction movements of the vehicle, however, both the vertical and longitudinal position of the wheel changes during vibration [17]. As a result, the forces due to the irregularity of the road will accelerate the body of the vehicle both longitudinally and vertically. Therefore, displacements along 3 axes need to be detected, which can be implemented in a compact form using an IMU sensor.

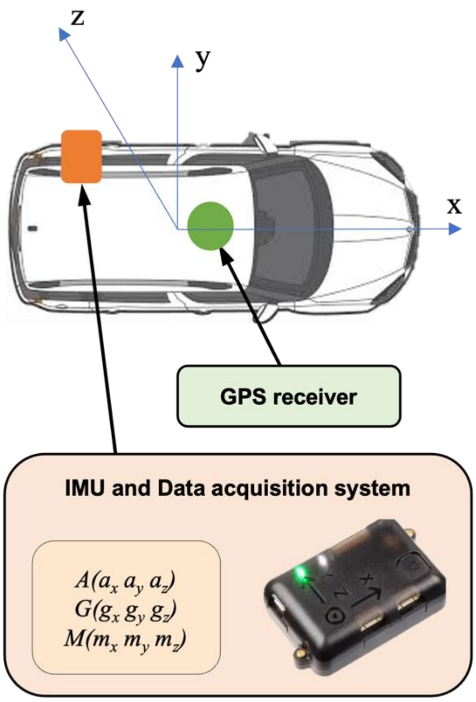
Previous studies have developed various methods for processing the raw measurement data from the cabin. The main part of the studies is based on the selection of relevant features and the fitting and validation of the machine learning model. Feature extraction can be used to reduce the dimensionality of the data sets, help extract relevant information and reduce irrelevant measurement noise and errors. Frequently used features are Fourier transform and frequency domain analysis and the related power spectral density-based classification. These reflects accurately to road irregularities and have a strong correlation between road unevenness and vehicle body ride vibration response [8][18]. Along with these, several studies have used principal component analysis for dimensionality reduction with good results. The classification algorithms applied have varied, with many using support vector machine, neural network or decision tree models. The average accuracy of these models is close to 85%, while the range is between 72% and 90%.

III. SUSPENSION VIBRATION BASED SOFTWARE SENSOR DEVELOPMENT

We have developed the system by considering the above aspects, the main details of which are presented in this chapter.

A. Applied measurement system

The device needs to be capable of tolerating any mechanical impacts, therefore a robust, compact, simple to install and operate type was required. The custom measurement system is based on an NGIMU unit from X-IO Technologies, which includes a 3-axis accelerometer, gyroscope and magnetometer sensor. A NEO-7M GPS unit was connected to the IMU unit via a serial communication link to record vehicle position data.



1. Figure Position of the sensors on the test vehicle

The IMU sensor is mounted on the rear control arm of the vehicle, so that there is no damping element between the wheel and the detector, and the vibrations are directly measured by the device. The positioning of the sensors on the test vehicle and the orientation of the axes is illustrated in Fig. 1. We installed the IMU sensor on the left side of the test vehicle, as our experience shows that the road surface on the outside is often worse, more degraded, with more frequent larger potholes. These give us a more realistic representation of the general condition of the road surface on the inner side.

B. Data processing and feature extraction

The first step of the data processing was the labelling of the raw data, where 3 classes were defined. Each category represents the road surface quality of each road section as follows:

- Class 1: The road surface requires urgent renovation, with large and deep defects continuously observed along the section. The road structure is characterised by sinkholes, subsidence, surface and deep potholes and cracks at the pavement edge.
- Class 2: The surface quality of the sections is medium and is expected to be reconstructed in the near future. Minor potholes and surface irregularities occurs.
- Class 3: Near fault-free pavement, section quality in good condition, no reconstruction work expected in the near future.

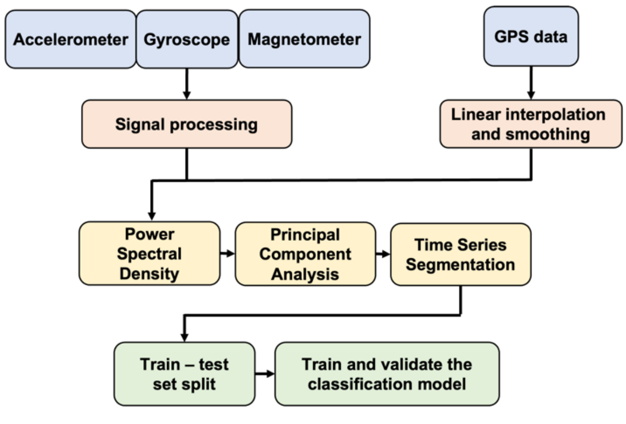
During data processing, it is necessary to resample the GPS signal, as its sampling frequency is lower than the vibration data. After this, the GPS data were smoothed to remove noise using a moving average filter. In addition, the vibration data were filtered using a highpass filter for detrending, thereafter the vibration and angular velocity measurement data transformed to the same scale using a min-max scaler. Furthermore, within the basic signal processing, the original time-dependent signal was resampled as a function of the distance travelled by the vehicle. Previous studies have shown that increasing vehicle speed increases the amplitude of the measured accelerations over the same quality surface. This effect can be reduced by distance-based resampling. The new data points were recorded at a distance of 0.35 m using interpolation.

Informative features are necessary to develop a well-performing machine learning model, for this, we transformed the vibration data from the time-domain into frequency-based data using power spectral density (PSD) analysis, in the form of a spectrogram. The Power Density Spectrum function transforms a signal from the time domain to the frequency domain and provides its frequency spectrum. Digital Signal Processing offers a lot of methods to extract this information, like Fast Fourier Transformation (FFT).

Following this principal component analysis (PCA) obtained dimensionality reduction and extract relevant information as well as reduce measurement noise. Principal component analysis was performed by centering the data and then performing a singular value decomposition algorithm. PCA helps to reflect the main aspects of the key variables, thereby providing improved possibility of segmentation of sections with different road pavement qualities. This requires the use of a time series segmentation algorithm based on series segmentation, which focuses on dividing the time series into appropriate, internally homogenous segments through rule discovery in the behaviour of the observed variable. The segmentation algorithm identifies abrupt changes in the series based on trimmed mean and variance features using a sliding window method. The accelerometer output of IMU sensors is commonly affected by high frequency and high amplitude noise, which in some cases is difficult to separate from the useful signal. Time series segmentation can be used to filter out these low duration but high amplitude data errors, as longer duration features will be dominant. The developed segmentation algorithm separates coherent sections based on the mean and variance of the data series. In order to validate the algorithm, we manually labelled the segment boundaries on the data series, and determined their position based on our visual observations. We were then able to verify the correctness of the automatic labelling.

C. Classification model

After performing time-series segmentation, each coherent section is classified into one of the three categories defined above. Several algorithms were tested, and the binary decision tree classifier provided the best accuracy. For finding the optimal algorithm, various split predictors, such as the CART, QUEST, and GUIDE algorithms have been examined, but the CART algorithm proved to be the most effective and was therefore chosen.



2. Figure Schematic overview of the data processing algorithm

The model is fitted in a supervised learning environment, validated by train-test set splitting method. The advantages of decision-tree based classification include simplicity to interpret, low data pre-processing requirements and low computational power, and that outliers have no meaningful effect, which is a significant consideration in our case. To ensure the robustness of the model, the dataset is split into a training and a test set in 70/30 ratio, where the training set is used to fit the model. Thereafter, the test set gives a sense of how the model performs on unseen data. The data processing and classification algorithm was developed in MATLAB environment and the schematic representation of the algorithm is shown in Fig. 2.

IV. RESULTS AND DISCUSSIONS

A. Measurement conditions

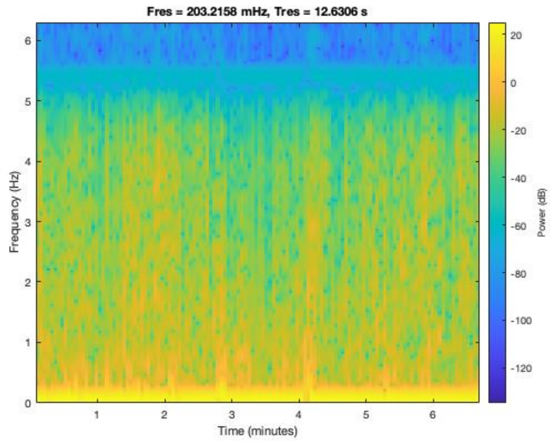
The measurement system was developed and tested in a real-world environment using two different passenger vehicles with significantly different suspension characteristics. A 2019 Nissan Leaf hatchback and a 1997 BMW 318is sedan were used. The former's rear suspension consists of a torsion beam with trailing arms and separate spring and damper, while the latter has fully independent multilink trailing arms and also separate spring and damper elements with much higher rigidity.

The measurements were carried out on predefined and public road network in both residential and suburban areas. This allowed measurements to be carried out on road surfaces of different quality, covering all categories, with varying vehicle speeds.

Furthermore, the system was tested with different placements of the IMU sensor, which was placed on the other side of the suspension and on different longitudinal control arms. However, the most accurate solution was obtained using the original placement.

B. Results of feature extraction and classification

Following the basic data processing steps, the power spectrum data showed the noticeable quality segment bands. The bands of PSD with higher power sections represent the lower quality pavement on which relative high amplitude vibrations are generated. The power spectral density spectrogram calculated for the Z-axis accelerometer sensor data series is shown in Figure 3. In these data, the different power sections mentioned above can be clearly observed, on the basis of which further work was discarded.



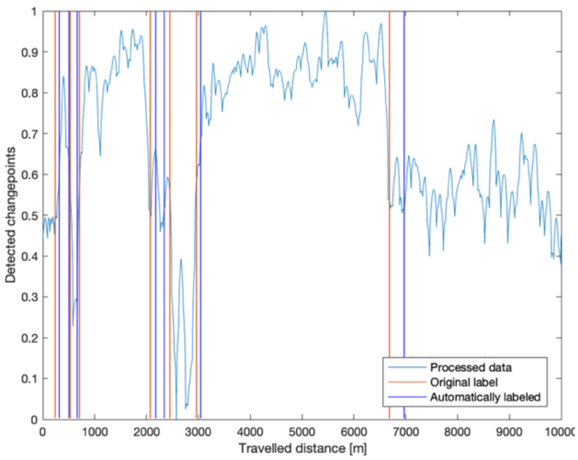
3. Figure Power spectrum of the IMU Z-axis accelerometer

The calculation of power spectral density was followed by principal component analysis, which helped to reduce the 9-dimensional data set into one dimension containing the information relevant for classification.

The PCA vectors represent the useful information content of each variable, and therefore meaningful data are the angular velocity around the gyroscope's X axis and the linear accelerations along the Y axis in addition to the accelerometer's Z axis. Furthermore, according to the orientation of the axes, they have different but useful information content. Furthermore, the PCA analysis shows that the first principal component account for 93% of the total variation, which means that the dimension of the dataset can be reduced with minor loss. Therefore, the original data set was further reduced to the first component score vector.

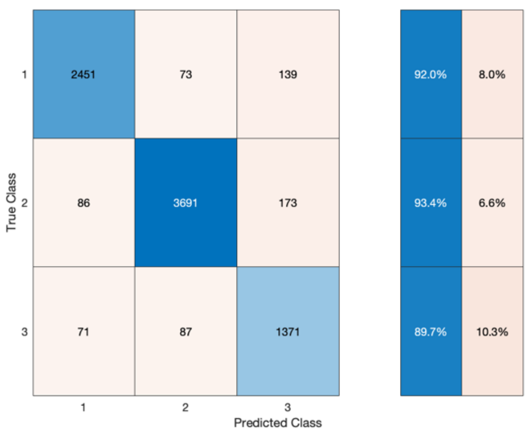
After the principal component analysis, the boundaries of each coherent section were determined using the time series segmentation algorithm, and subsequently the binary classification decision tree model was fitted.

The labelled and detected changepoints with the time series segmentation algorithm are shown in Fig. 4, where the data series as input to the algorithm is also displayed. From the figure it can be observed that the boundaries of the original segments marked in red and the detected segments marked in blue are well matched, with only a few minor deviations.



4. Figure Detected changepoints and the original labelled points according to time series segmentation

After the time series segmentation algorithm was developed, the classification model was designed and optimized. In this context, to prevent overfitting, pruning method has been applied to set the optimal depth of the decision tree model, furthermore the optimal hyperparameter settings have been determined. The maximum depth of the decision tree model is 14, a reduction of about 12% compared to our previous system. Training and validation have been performed using the train-test split method. The accuracy of the model based on the test dataset for unseen data is near to 92% according to confusion matrix, and the highest number of misclassifications occurred between Class 2 and 3. The model confusion matrix is illustrated in Fig. 5, which also shows the locations of misclassification. Furthermore, it can be seen that most of the data values fall into the second class, as this medium-quality road surface was the most frequent during the test drive.

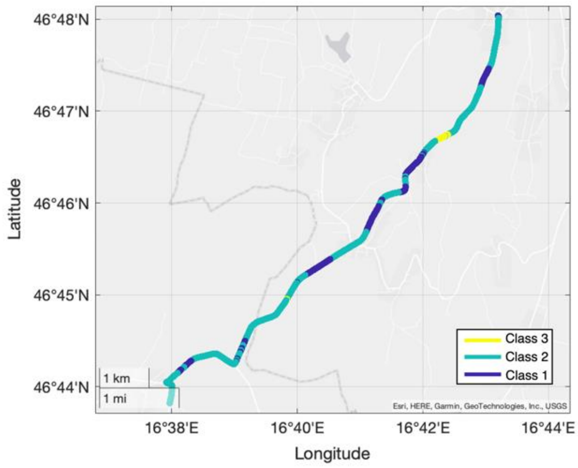


5. Figure Confusion matrix of the machine learning model

C. Results of public road measurements

The developed system using the developed classification algorithm was tested on the surface of public roads, on predefined routes not included in the training stage. The total testing distance for the two vehicles was more than 100 km. For further validation, the test phases were performed three consecutive times and the classification results were compared.

The measured quality of a suburban section is shown in Fig. 6 in map visualisation, where the route is represented by the three colours for each class. During the test case, speeds typically varied between 50 and 90 km/h per hour, and this measurement was carried out with the sedan type vehicle.



6. Figure Measurement results of a suburban road section in map visualisation

The results of the measurement show that there are several degraded road sections, some of which are in urgent need of reconstruction. Only a short area is observed to be of good quality. The measurement result is consistent with our visual observations, with numerous potholes, cracks and surface depressions observed during the measurement.

On this road section, the measurement was also carried out three times per vehicle and the results were compared. The comparison was made by road quality class, based on the length of each section. Their mean and standard deviation are shown in Table 1.

1. Table Sum of mean and standard deviation of segment lengths, according to pavement quality classes

	Sum of mean segment lengths [km]	Standard deviation of segment lengths [km]
Class 1	4.3	0.2
Class 2	11.2	0.9
Class 3	0.8	0.1

The results show that the largest variance was in the Class 2 category, while the Class 1 class showed the largest proportional similarity. This can be explained by the typical good and clear separation of the worst quality sections from the other two classes.

V. CONCLUSIONS

In our study we presented the development of a measurement system for pavement surface quality.

Previous studies have focused on the development of simple road quality measurement devices, often based on a mobile phone. However, in our previous work we have shown that measuring on a suspension has a more relevant information content, with clearer signals being observed.

Based on this, the current system is based on an IMU sensor mounted on a suspension of test vehicles, which allows to increase its accuracy. The data processing and classification of each individual section is performed with the support of software sensor and machine learning algorithm. The signal processing system includes a time series segmentation algorithm to filter outliers. The dataset dimension is further reduced using principal component analysis. By positioning the IMU sensor on the axis, we have been able to reduce the size of the classification algorithm compared to our previous system, which can reduce the computational requirements.

Real test measurements with two vehicles following validation showed good results, with good agreement with our visual inspections, making us confident that the developed IMU could be a good and cost-effective alternative for measuring road surface quality on lower-grade roads.

VI. ACKNOWLEDGMENTS

This research was supported by the National Research, Development, and Innovation Office of Hungary under the project „Research and development of safety-critical brake-by-wire brake systems and intelligent software sensors that can also be used in autonomous vehicles" (project code: 2020-1.1.2-PIACI-KFI-2020-00144)

This work has been implemented by the TKP2020-NKA-10 project with the support provided by the Ministry of Culture and Innovation of Hungary from the National Research, Development and Innovation Fund, financed under the 2020 Thematic Excellence Programme funding scheme.

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