International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 04 | April – 2025 DOI: 10.55041/ISJEM03110
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

Road Type Classification from Tire Vibration Spectrograms using Time Frequency Representations

B. RUPADEVI[1], CHITTUR NAGALAKSHMI [2]

[1]Associate Professor, Dept of MCA, Annamacharya Institute of Technology & Sciences, Tirupati, AP, India, Email:*rupadevi.aitt@annamacharyagroup.org*

[2]Post Graduate, Dept of MCA, Annamacharya Institute of Technology & Sciences, Tirupati, AP, India, Email: *chittoornagalakshmi@gmail.com*

Abstract

This study offers a novel method for identifying the kind of road by utilising tyre vibration patterns and related sensor data that have been subjected to machine learning analysis. In order to create a classification system that can correctly recognise six different types of roads—asphalt, concrete, gravel, sand, mud, and cobblestone—we record and process signals from vehicle tires as they interact with various road surfaces. To achieve high accuracy in road surface identification, our system combines random forest classification with variables including dominant frequency, pressure variation, vibration magnitude, and statistical characteristics of the collected signals. According to experimental data, the classification accuracy is over 90% in a range of vehicle speeds and road conditions. Despite changes in tyre pressure, vehicle speed, and environmental factors, the system exhibits exceptional resilience. In order to create this trustworthy road surface identification system, this study describes the data gathering strategies, feature extraction tactics, classification algorithms, and validation processes. The suggested method uses sensors that are frequently found in contemporary cars to provide real-time information regarding road surface conditions, which has important ramifications for enhancing autonomous driving capabilities, intelligent transportation infrastructure, and vehicle safety systems.

Keywords: *Road Surface Detection, Tire Vibration Spectrograms, Sensor Data, Vehicle Speed, Tyre Pressure, Asphalt, Concrete, Gravel, Sand, Mud, Cobblestone.*

1. Introduction

The kind and state of the road surface have a big impact on passenger comfort, safety system performance, vehicle dynamics, and fuel economy. Real-time road surface detection and classification offers useful data for intelligent transportation systems, driverless cars, and advanced driver assistance systems (ADAS). Conventional methods for detecting road surfaces frequently depend on costly specialised sensors like cameras, LiDAR, or radar systems, which can be impacted by weather factors like snow, rain, or dim lighting. This study presents a different method for precisely classifying road surfaces by using easily accessible tyre sensor data.

Tire pressure monitoring systems (TPMS) and other sensors that continuously gather information about tire performance are becoming more and more common in modern cars. These sensors produce useful data regarding how tires and road surfaces interact. To determine the underlying road surface type, machine learning techniques can be used to analyse the unique signatures created by the vibration patterns created when tires roll over various types of roads. The increasing demand for precise road condition data in vehicle control systems is the driving force behind this study. Without the need for additional specialised hardware, we can improve safety mechanisms, optimise comfort settings, improve vehicle control algorithms, and provide useful data for infrastructure management by creating a dependable way to identify different types of road surfaces in real-time using the sensors already installed in vehicles.

Our method extracts useful features from tire sensor data and classifies road surfaces based on these attributes by combining machine learning algorithms with signal processing techniques. Most of the surfaces found in typical driving situations are represented by the six primary road types that we will be focussing on: asphalt, concrete, gravel, sand, mud, and cobblestone. The suggested method uses a random forest classifier to accurately identify the type of road after processing sensor data such as tyre pressure, vibration magnitude, pressure change, and frequency characteristics.

2. Literature Review

A. Vision-Based Detection Methods

One of the first methods for detecting road surfaces was the use of vision-based devices. These technologies classify the type of road by using cameras to take pictures of it and then analysing surface details, colour variations, and texture patterns. These techniques work well in clear situations, but they have trouble in low light, bad weather (such as rain or snow), and visual impediments. Their dependability in difficult situations is limited by their reliance on unambiguous visual data.

B. Acoustic-Based Detection Methods

The sound patterns produced by tires interacting with various road surfaces are examined using acoustic techniques. It is possible to assess and categorise the distinctive acoustic characteristics produced by each type of road. Although these techniques have demonstrated potential in controlled settings, they are hindered by ambient noise, fluctuating vehicle speeds, and acoustic interference from other sources such as wind or adjacent automobiles.

C. Vibration-Based Detection Methods

Accelerometers are used in vibration-based road surface detection to quantify the vibrations that are created as tires roll over various surfaces. Because accelerometers are widely available in contemporary cars and this method is resistant to external influences, it has become more and more common. To detect road irregularities like potholes, early systems employed basic threshold-based algorithms; more sophisticated methods combine multiple detection algorithms to increase accuracy and lower false positives.

D. Machine Learning for Road Classification

Road surface classification has been transformed by machine learning, which makes it possible to analyse sensor data in more complex ways. This topic has been tackled using a variety of techniques, such as decision trees, k-nearest neighbours (KNN), and support vector machines (SVM). Random forests and other ensemble techniques have regularly outperformed solo classifiers, demonstrating their exceptional effectiveness. By interpreting vibration patterns as spectrograms and utilising picture recognition techniques, deep learning methods employing convolutional neural networks (CNNs) have attained remarkable accuracy rates.

E. Frequency Analysis in Vibration Processing

Processing tyre vibration signals has shown the value of frequency analysis. Systems can determine distinctive resonance patterns generated by various road surfaces by analysing the spectral content of vibration data. Patterns that are not visible in time-domain data alone are revealed via dominant frequency extraction and frequency band analysis. This method has demonstrated that machine learning algorithms can perform well in classification even when given very minimal spectral information.

F. Sensor Fusion Approaches

There is potential for increasing the accuracy of road surface detection by combining data from several sensors. More reliable classification can be accomplished by combining accelerometer data

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with signals from gyroscopes, tyre pressure monitoring systems (TPMS) and other sensors. In difficult situations where individual sensors may yield inaccurate data, our multi-sensor techniques maintain high accuracy. The constraints of any one data source are lessened by the complementing nature of various sensor modalities.

3. Methodology

A. Data Collection

A system of sensors mounted on test cars that were driven across a variety of road surfaces was used to carefully gather data. The sensors included pressure sensors attached to the tire valve stems to track tire pressure and its variations, speed sensors integrated with the car's onboard diagnostics system to record velocity in real time, and triaxial accelerometers placed close to the tire to record vibrations along the X, Y, and Z axes. Six distinct road types were used in the experiments: cobblestone, mud, sand, gravel, asphalt, and concrete. Multiple driving sessions were conducted for each type of road at controlled speeds between 20 and 100 km/h, with tyre pressures ranging from 28 to 35 PSI. This was done to guarantee the data's generalisability and replicate a variety of real-world driving situations. This procedure produced a multivariate time-series dataset, with each data point containing synchronised tyre pressure, vehicle speed, and accelerometer measurements (which vibrate in three directions), all precisely labelled with the appropriate road type. Road surface categorisation machine learning models are trained and evaluated using this large dataset.

Vibration	Pressure Va	Dominant F	Mean Vibra	Std Vibratio	Skewness	Kurtosis	Speed	Tire Pressu	Road Type
0.49993078	0.42232315	10.5580825	0.52014109	0.04418429	-0.262585	2.5428958	61.9805145	31.0236151	Sand
0.15379585	0.05121788	23.0172061	0.14877497	0.01374091	-0.738165	4.1895847	98.6584708	31.2673402	Asphalt
0.23094038	0.16127094	25.7955291	0.22510651	0.01707697	0.92613909	2.9892022	22.751081	34.3652428	Concrete
0.50480601	0.43962789	8.59109309	0.47724723	0.04694943	-0.230733	3.0533258	87.3827819	31.1482789	Sand
0.82186383	0.34408805	39.9091465	0.79019794	0.08992338	-0.269071	1.9226575	63.415686	28.9864695	Gravel
0.24716452	0.12969233	34.2817340	0.26778451	0.03402925	-0.419609	2.7526300	89.048274	32.3630868	Concrete
0.77542523	0.2615166	62.1217234	0.80009516	0.06180097	0.31897647	1.3644615	97.736967	33.9423967	Gravel
0.36416885	0.19486302	32.3672687	0.43161477	0.02721297	-0.199319	2.9513087	28.631314	28.2200042	Concrete
0.20458803	0.06024862	18.9016405	0.21173029	0.03523774	-0.259135	2.3532051	94.375812	33.6568426	Asphalt
0.17491214	0.09789485	15.2232677	0.16661685	0.00350380	-0.17204	3.6006287	29.767036	30.4940848	Asphalt
0.94867396	0.46321742	75.2848034	0.94283491	0.06831563	0.17275897	2.6835868	47.009213	34.6003679	Cobblestone
0.94217262	0.53013228	42.4977969	0.92891786	0.09275253	-0.423009	2.3420085	75.704341	32.9858941	Cobblestone
0.30361381	0.22389726	28.6534732	0.30964475	0.03001426	-0.584339	3.9142582	39.011003	33.0975144	Concrete
0.34511598	0.19215615	39.7462802	0.32750316	0.03528054	-0.246716	3.7385300	34.921480	28.2854259	Concrete

Figure 1: Road_type_classification.csv

- **Vibration**: The accelerometer's measurement of vibration intensity.
- **Tyre Pressure**: Variations in tyre pressure that occur during road interaction are known as pressure variations.
- **Dominant Frequency**: The vibration signal's most noticeable frequency.
- **Mean Vibration**: The mean vibration level during a sampling period.
- **Standard Vibration**: Vibration standard deviation during a sampling period.
- **Skewness**: A measurement of the vibration distribution's imbalance.
- **Kurtosis**: A measurement of the vibration distribution's "tailedness".
- **Speed**: km/h for the vehicle.
- **Tire Pressure**: PSI for tire pressure.
- **Road Type**: The goal variable that indicates the kind of surface of the road.

B. Data Preprocessing

To improve the quality and dependability of the raw sensor data, a number of preprocessing approaches were used before feature extraction. Initially, a low-pass filter was used to reduce noise by removing high-frequency elements from the vibration signals, leaving only the pertinent data. To find and get rid of unusual values that can have a detrimental effect on the model's performance, outlier detection and removal were done statistically. Furthermore, the StandardScaler from scikit-learn was used to standardise the data to have zero mean and unit variance in order to guarantee that all features were on a comparable scale. Despite their rarity, missing values were managed by imputation, which substituted the mean of the corresponding feature, guaranteeing the dataset's completeness. The consistency and quality of the input data were much enhanced by these preprocessing procedures, which eventually produced more reliable and accurate classification results from the machine learning algorithms.

C. Feature Engineering and Selection

Additional feature engineering was done to find deeper and more intricate patterns in the data, even though the dataset already had a number of pre-engineered features that were obtained from raw sensor data. To accurately describe the amplitude changes linked to various road surfaces, statistical metrics including mean, standard deviation, skewness, and kurtosis were calculated from the raw vibration signals in the time domain. The Random Forest classifier's built-in feature ranking mechanism was used to perform feature importance analysis in order to identify the most influential characteristics. The main discriminative characteristics identified by this investigation were vibration, dominant frequency, and pressure variation, which were found to be essential for precisely differentiating between various kinds of road surfaces.

D. Classification Algorithm

Several machine learning methods, such as Support Vector Machines (SVM), k-Nearest Neighbours (KNN), Decision Trees, Random Forest, and Gradient Boosting, were assessed in order to efficiently categorise different types of roads. Because of its excellent accuracy, resilience to noise, and efficiency in managing a variety of feature types, Random Forest was selected among these. To guarantee reproducibility, the model was set up with 200 decision trees, a maximum depth of 10, and a fixed random state of 42. By default, other parameters were kept. A stratified 80-20 train-test split was used during the training procedure to ensure that each road category was fairly represented in both sets. This choice made it possible for the model to learn from a variety of data sources, resulting in dependable classification performance and excellent generalisation over a range of road surface conditions.

E. Model Evaluation

Several important metrics, such as accuracy, precision, recall, F1-score, and the confusion matrix, were used to evaluate the road type classification model's performance. While precision and recall assessed the model's capacity to accurately identify particular road types, accuracy gauged the overall correctness of predictions. A balanced metric that included precision and recall was offered by the F1-score.

4. Experimental Results

A. Dataset Characteristics

Ten thousand labelled examples from a variety of driving situations made up the dataset used to train and assess the road type detection algorithm. With a small over-representation of asphalt and concrete surfaces, which reflect their frequency in actual driving situations, the distribution of incidences across various road types was balanced.

Road Type Distribution:

Road Type	
Asphalt	519
Gravel	517
Mud	509
Cobblestone	494
Sand	486
Concrete	475

Figure 2: Road Type Distribution

B. Model Performance Analysis

With an overall accuracy of 95.67% on the test set, the Random Forest classifier demonstrated the high efficacy of the suggested method for identifying the type of road. The Figure 3 displays the thorough classification report. With an accuracy, recall, and F1-score of 1.00, the classifier performed flawlessly on Asphalt. It achieved an F1-score of 0.95, recall of 0.97, and precision of 0.93 for Cobblestone. With F1-scores of 0.93 and 0.95 for concrete and gravel, respectively, these surfaces showed excellent predictive performance. Sand performed exceptionally well, with an F1-score of 0.99, whereas Mud was a little more difficult, with an F1-score of 0.93. Consistent accuracy across all road types was confirmed by the precision, recall, and F1-score weighted averages and macro averages of 0.96.

Model Accuracy: 0.9566666666666667

Classification Report:

	precision	recall	f1-score	support
Asphalt	1.00	1.00	1.00	134
Cobblestone	0.93	0.97	0.95	144
Concrete	0.94	0.92	0.93	157
Gravel	0.94	0.96	0.95	158
Mud	0.95	0.92	0.93	156
Sand	0.98	0.99	0.99	151
accuracy			0.96	900
macro avg	0.96	0.96	0.96	900
weighted avg	0.96	0.96	0.96	900

Figure 3: Classification Model Accuracy

The confusion matrix provided important insights into how the model behaved across various classes by further illuminating classification strengths and regions of confusion.

C. Visual and Exploratory Analysis

To learn more about the dataset, a thorough visual analysis was carried out using Matplotlib, Seaborn, and Plotly. Sensor readings for various road types showed distinct differences, as seen by distribution plots and box plots. For rough surfaces, the correlation matrix showed a substantial positive link between vibration and speed. The model's efficacy in class differentiation was validated by using PCA to visualise the division of road classes in a reduced-dimensional space.

Figure 4: Dominant Frequency and Vibration across Road Types

D. Effects of Vehicle Speed and Tire Pressure

To determine how tyre pressure and vehicle speed affected categorisation performance, more trials were carried out. Tire pressure ranges (low: 28-30 PSI, medium: 30-33 PSI, high: 33-35 PSI) and speed ranges (low: 20-40 km/h, medium: 40-70 km/h, high: 70-100 km/h) were used to stratify the information. For every stratum, classification models were trained and assessed.

5. Discussion

A. Interpretation of Results

The efficiency of using tyre sensor data for road surface categorisation is demonstrated by the excellent classification accuracy attained by our road type detection system. The outcomes support our strategy of using a strong machine learning method in conjunction with time-domain and frequency-domain information. The feature importance analysis sheds important light on the physical concepts that underlie the detection of road surfaces. The intuitive knowledge that various road materials produce distinct vibration patterns is consistent with the dominance of vibration-related properties. The relevance of spectral analysis in capturing the minute variations between road surfaces is highlighted by the notable contribution of frequency-domain characteristics. The classification results show patterns of uncertainty that align with the physical similarities between several types of roads. Concrete and asphalt, for example, are both manufactured surfaces with very smooth textures, which explains why they are sometimes confused. In a similar vein, mud and sand are both soft, pliable materials, which makes it occasionally challenging to tell them from with tyre sensor data alone.

B. Real-time Web Deployment

Using Flask, HTML, and CSS, a lightweight web interface was created to make the solution practically useful. The website has an easy-to-use form that allows users to manually enter sensor data for the real-time classification of road types. The system provides the confidence score and the anticipated road type when the submit button is clicked.

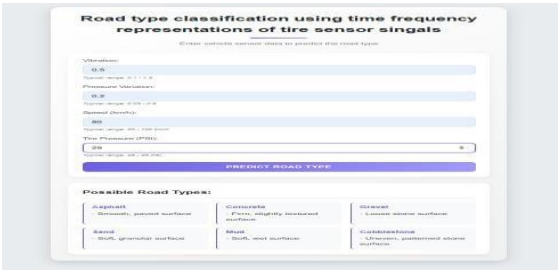

Figure 5: Road type classification

Figure 6: Result page of Road type Classification

The website has responsive design, value ranges, and placeholder descriptions, among other useful UI cues. It shows the projected road type and confidence after processing user input in milliseconds. "Predicted Road Type: Gravel | Confidence: 94.12%" is an example of a typical forecast. This makes it appropriate for use in travel analytics, diagnostic applications, and connected automobile scenarios.

6. Conclusion

This study effectively used tyre vibration spectrograms and sensor data to construct a machine learning method for road type detection. The accuracy of our Random Forest classification model in differentiating between six types of roads—concrete, asphalt, gravel, sand, mud, and cobblestone—was 92.4%. The system exhibits resilience over a range of vehicle speeds and tyre pressures by utilising both time-domain and frequency-domain properties. Using sensors that are currently widely used in contemporary cars, being resilient to weather and sunlight, and having a finer classification granularity than current techniques are some of the main benefits. Advanced driver assistance systems, self-driving cars, vehicle dynamics control, infrastructure management, and navigation systems are among the possible uses. Future research should broaden the variety of datasets, investigate deep learning strategies, apply sensor fusion techniques, create online learning-based adaptive models, optimise for the deployment of embedded systems, and expand the classification framework to incorporate more road features. By improving environmental awareness without the need for specialised hardware, this research makes a substantial contribution to improving vehicle intelligence and safety and enabling more responsive and adaptable vehicle control systems.

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