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DETECTING ROAD DAMAGES BY USING GYROSCOPE SENSOR

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Abstract. *This study focuses on developing a simple three-layer Artificial Neural Network (ANN) model for automatic classification of road anomalies. The model is particularly important to facilitate the development of the road condition monitoring system. We limit the discussion to the system that utilizes vehicle vibration data to predict the associated road condition. The vibration data are obtained from a probe vehicle running over four road types: a road in a good condition, a road containing a pothole, a road containing a speed bump, and a road containing an expansion joint. The data are then used to extract the vehicle maximum rates of rotations in three directions: pitch, roll, and yaw. This study reports the aspects of the optimum size of the training data, the effects of the number of the neurons in the hidden layer, and the level of the achievable classification accuracy. The results show the optimized model with three neurons on the hidden layer is able to correctly classify damages at 85% accuracy.*
Keywords: Road anomalies, Damage classification, Artificial neural network (ANN), Gyroscope

1. **Introduction.** In 2009, Indonesia legislated the law number 22 regarding traffic and transportation [1]. The law stipulates that the road administrator should immediately repair any damaged road that can lead to traffic accidents. If they are not able to do so, they oblige to put signs on the damaged road to prevent the occurrence of traffic accidents. For any traffic accident, the road administration may be imprisoned for a duration of six months up to five years or fined for an amount of 12 million rupiah up to 120 million rupiah depending on the victim conditions.

For the reason, the road administrator should consider the maintenance of the road conditions to the utmost degree. Thus, the road administrator needs an information system that can provide the roads status of the entire road network in a timely manner. By considering the pervasiveness of the road network particularly in the metropolitan city such as Jakarta, it is extremely difficult and time consuming to monitor the road condition manually [2]. The manual road monitoring is not only difficult but also very dangerous.

Several researches regarding automating damaged road detection have been undertaken. They have evaluated various detection schemes including the 3D pavement reconstruction methods [3, 4], laser imaging method [5, 6], computer vision techniques [7, 8], and vibration-based methods [9, 10, 11, 12, 13]. Some of those methods require special devices making them uneconomical and difficult to implement practically.

In this field, many recent publications proposed methods developed based on image processing. These developments can be classified according to the size of the damaged area that is covered and the type of the damages. [14, 15, 16] developed methods to observe damages in wide area such as disconnected road segments due to earthquake.

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Many proposed techniques are proposed for observing and quantifying damages in narrow area on road segments such as cracks [16, 17, 18], and potholes and spallings [19, 20, 21].

To cover wide observation area, [14] developed a system to classify damages on roads and building due to earthquake based on satellite images prior and after the event. Some computational intelligence methods were used to generate damage features and to classify the damage types. In addition, [15] proposed a method to detect road discontinuity based on remote sensing images. Finally, [16] developed a method to detect crack and surface damage due to earthquake for a robot.

To cover narrow observation area, [17] evaluated the use of random structured forests to detect cracks on concrete. Moreover, [18] proposed MorpLink-C algorithm that uses a neural network to improve the crack detection. [19] developed a neural network model to detect potholes. [20] developed a method to detect patches on pavements.

[22] provided a comprehensive list regarding image processing methods as well as computational intelligence methods that have been studied for the purpose of damage detection and classification in civil infrastructure.

As demonstrated in [9, 10, 11, 12, 13, 23], the vibration-based method has the potential and can be implemented using low-cost mobile devices. The method has been evaluated in conjunction with a simple road damage classification method [12]. In [24], the classification is performed by an Artificial Neural Network (ANN) model.

In this work, the vibration-based method is studied further by taking into account the data obtained by gyroscope sensor. To the best of our knowledge, the majority of the previous vibration-based methods relied on accelerometer data [2, 9, 12, 24]. Both the gyroscope and accelerometer sensors are also widely available in many modern smartphones. Thus, the current method is scalable and can be implemented at a low cost.

The manuscript has the following structure. Section 2 describes the research procedure including the data collection and analysis methods. Section 3 presents the data recorded by the gyroscope for a normal road and damaged roads, the accuracy of the road-damage classification, and the most relevant feature data. Finally, Section 4, outlines the salient findings of this work and a proposal for future works.

2. **Research Method.**

2.1. **The decision tree-based method.**

A simple vibration-based road damage classification scenario was proposed by [9]. It was based on a decision tree. The path to the decision regarding the types of road anomalies is reproduced in Figure 1. The decision making process is described in the following.

The main data for detection were the vehicle acceleration in the vehicle lateral direction (x) and vertical direction (z). The longitudinal direction is assumed to be insensible to the damage. The lateral direction is in respect to the vehicle-side direction.

The detection is performed in the following sequences. The detection began by recording a stream of the 256 acceleration data. However, firstly, the vehicle velocity was evaluated;

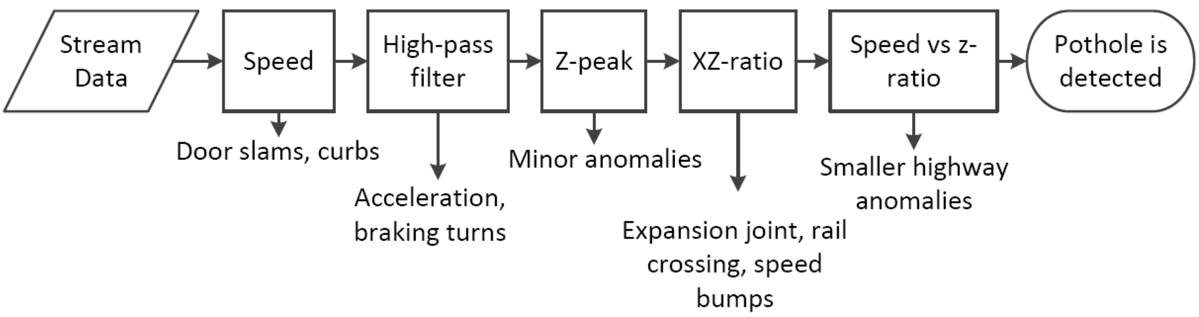


FIGURE 1. The flowchart of the pothole detection procedure [9]

if it was too low, the stream of the data would be ignored, and a new stream of the data would be taken. If the stream data passed the previous velocity checking, the data would be filtered with a high-pass filter. Subsequently, only the z direction acceleration data (a_z) were evaluated against a threshold, t_z. The data stream would be further processed if the maximum of a_z ($a_z^{\max}$) exceeded t_z; otherwise, a new data stream would be taken. Next, the x direction acceleration data within the time interval centered at the time of $a_x^{\max}$ was evaluated for its largest value ($a_x^{\max}$). The interval width was 32 data. Again, this extreme value would be checked against a threshold t_x; and similar to the previous rule, if $a_x^{\max} < t_x$, the data stream ignored and new one would be taken. The last evaluation was that to reject the data stream if $t_z^{\max} < t_s \cdot v$, where t_s is the threshold and v is the vehicle traveling velocity.

The current proposal differs from the previous method in two aspects. First, the current method uses the rates of rotation data collected by gyroscope instead of the acceleration data. Second, the classification is performed by an ANN model instead of a decision tree.

2.2. **Data acquisition process.** The data for the current study are collected and analyzed according to the following procedure. The data are collected by using 3D gyroscope sensors on a smartphone at the sampling rate of 5 ms. The smartphone and its coordinate system are shown in Figure 2. The phone is then glued to the dashboard of a vehicle. The attention is given on the elevation and alignment of the phone with respect to the vehicle coordinate system. The type of used vehicle is Toyota Avanza (see Figure 3).

The y-axis aligns with the vehicle longitudinal direction, positive pointing to the vehicle front side. The x-axis aligns with the vehicle lateral direction. The z-axis aligns with the vehicle vertical direction. We note that according to [12], the recorded vibration in x- and z-directions are crucial for detecting the pothole. When one of the vehicle tires enters a pothole, the vehicle undergoes vibration in the two axes.

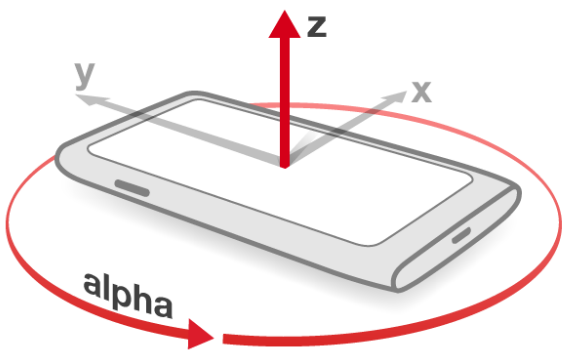


Figure 2. The coordinate system of the used smartphone. The z-axis aligns with the vehicle vertical direction, x-axis with the lateral direction, and y-axis with the longitudinal direction.

Figure 3. The used vehicle in the data collection

Two types of smartphones are used to record the vehicle rates of rotation data. They are OnePlus One (Device A) and Lenovo P70 (Device B). Device A is placed on the car dashboard. Meanwhile, Device B is in the middle section of the car floor in front of the second row car seats. A third party software, AndroSensor, is used to record the data. The application records the data and saves them in csv-file format.

The test vehicle is driven to travel along a road in good condition, and a road containing a pothole, a speed bump, and an expansion joint. Those road anomalies are located separately, so each anomaly can be measured uniquely. The test vehicle is maintained at the velocity of 3 m/s and 6 m/s. For each setting, the experiment is repeated for 60 times. These settings are approximation and only controlled by a visual examination of the vehicle odometer. The pothole is produced artificially by removing some paving blocks. The hole is varied in size as a small hole with a length of 20-30 cm and a big hole with a length of 40-60 cm. The vibration data are recorded for a travel distance of 10 m, approximately. The vehicle hits the road anomalies at around the middle of the travel distance.

Prior to the extraction of the data, a number of pre-processes are applied to the data. First, it is the zero shift where the recorded data are subtracted with its mean value. This process is applied to the data in the three directions: x, y, and z. Second, the data are filtered using a low-pass filter called Savitzky-Golay filter [25] with the first polynomial order and the frame size of 41. We establish a window having a length of 64 points centered on the time when the test vehicle hits the road anomaly. Those data in the window are subjected to a Hamming window and transformed into the frequency domain using the fast Fourier transformation [26].

2.3. **Damage sensitive features and neural network model.** The maximum of the vehicle rotation rates in the vertical and lateral directions are considered to be the main features of the vehicle vibration. It can strongly be related to the road anomalies. In addition, we also take into account the dominant frequency associated with the vehicle rotations.

ANN is used as the classification method because of its capability to learn from examples and capture the functional relationships among the hard description of data. The network is a multilayer back-propagation network. This network uses sigmoid as its activation function. Network parameters such as percentage of training data and number of hidden layers are varied to establish the most optimum network model. The detail of the model is described in Table 1.

Table 1. The parameters and their values related to the three-layer artificial neural network model in the study

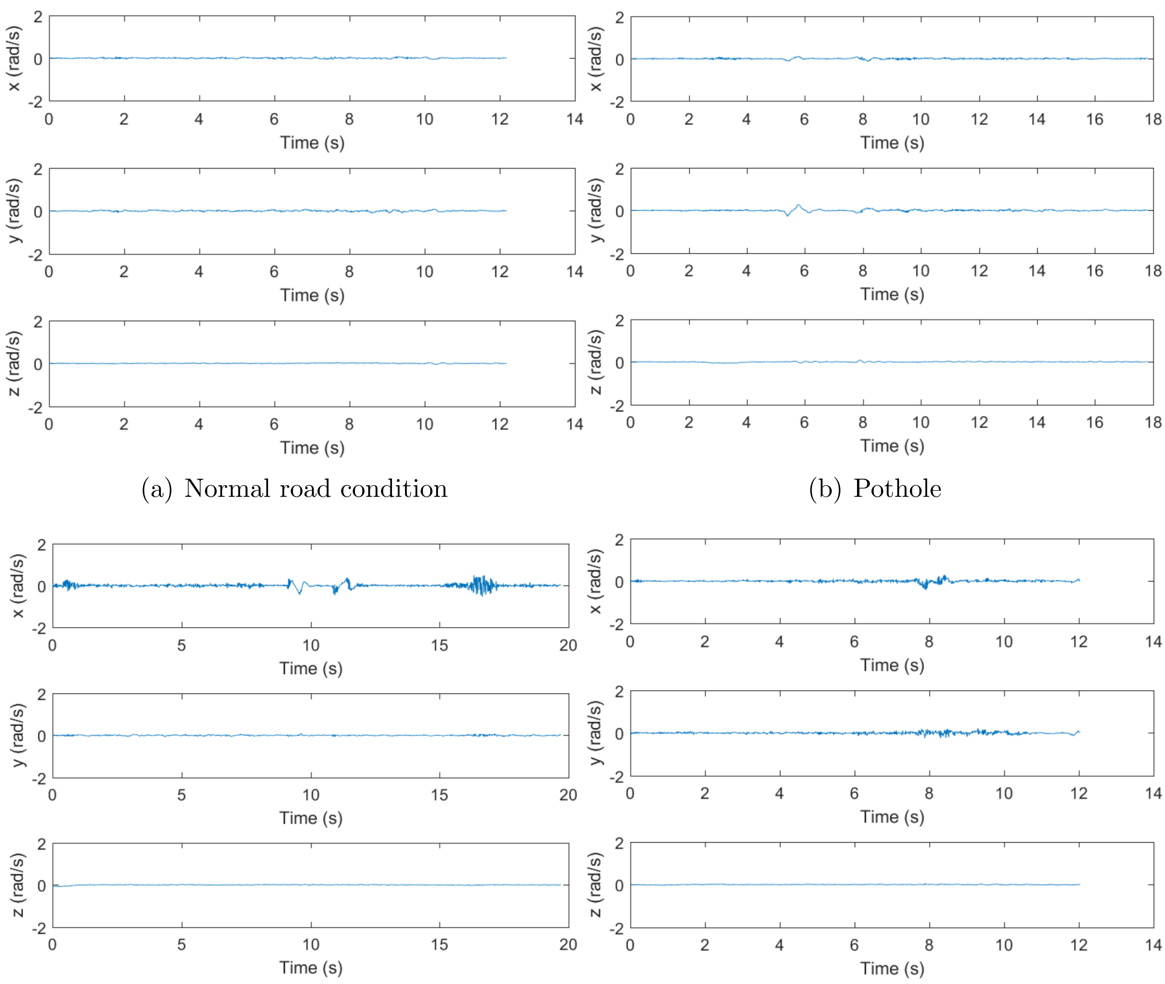
Parameter	Value
Activation function	Sigmoid
Learning rate	0.3
Momentum	0.2
Epochs	10000
The number of neurons in the hidden layer	2-9
The portion of data for the training	10-90%
The portion of data for the validation*	50%
The portion of data of the testing set*	50%

*The percentage is with respect to the remaining data. For example, if the training phase utilizes 60% of the data, the remaining 40% data are equally divided for the validation and testing phases.

3. **Results and Discussion.** Firstly, we discuss how the gyroscope in the probe vehicle is responding to each of the road anomalies. The typical responses recorded by the gyroscope when the probe vehicle crosses each of the road anomalies are presented in Figure 4. The figure contains four panels where each panel shows the responses in the three vehicle axes: x-, y-, and z-directions. Those directions are related to the vehicle lateral, longitudinal, and vertical directions. Thus, the rate related to the x direction denotes the vehicle rate of pitch. Similarly, the y- and z-directions denote the vehicle rates of rotations in roll and yaw.

The data in the figure show the following phenomena. When the probe vehicle runs across the normal road, no significant vehicle rotations in the three directions are recorded by the gyroscope sensor. This sample of data shows that the maximum pitch rate is as low as 0.09 rad/s. Similarly, the maximum roll and yaw rates are as low as 0.08 rad/s and 0.0069 rad/s, respectively. These data also suggest that the yaw rate is weakly affected by the vehicle movement.

Figure 4(b) shows the typical vehicle rates of rotations when the vehicle runs over a pothole. We witness significant vehicle rotations in pitch and in roll. This sample of data shows the maximum pitch rate reaches a value of 0.15 rad/s. Notably, the maximum roll



(a) Normal road condition (b) Pothole

(c) Speed bump (d) Expansion joint

FIGURE 4. The typical recorded vehicle rates of rotations in x-, y-, and z-directions when the the probe vehicle runs over a normal road condition, a road with a pothole, a road with a speed bump, and a road with an expansion joint. Those directions are related to the vehicle pitch, roll, and yaw, respectively.

rate is even higher at the value of 0.28 rad/s. Finally, we note that the maximum yaw rate is still extremely low at 0.0016 rad/s.

Now, let us shift our focus to the case of speed bump. The relevant data are presented in Figure 4(c). This sample data show the vehicle maximum pitch rate reaches an extremely high value of 0.48 rad/s. Meanwhile, the rates of roll and yaw rotations are negligible.

Finally, we look closely to Figure 4(d) that presents the data for expansion joint case. In this sample of data, the maximum pitch rate reaches a value of 0.3048 rad/s and the maximum roll rate at the value of 0.2021 rad/s.

From our observations on the effect of the road conditions to the vehicle rotation rates, we conclude the following (see Table 2). The vehicle pitch rate is affected by the three road anomalies, namely, pothole, speed bump, and expansion joint. Speed bump leads to the fastest vehicle rate of rotation. A significant rate in roll occurs when the vehicle hits a pothole.

Table 2. The effects of the road conditions to the vehicle rotations in the three directions: x (pitch), y (roll), and z (yaw). More '×' means larger effect.

Road Anomalies	Vehicle Directions		
	x (Pitch)	y (Roll)	z (Yaw)
Normal	–	–	–
Pothole	×	××	–
Speed Bump	×××	–	–
Expansion Joint	××	×	–

Next, we extract the maximum rates of rotations from each direction and use them to develop an ANN model for classifying the damage types. In addition to the rate data, we also extract the dominant frequencies by using the fast Fourier transform [26]. The data of rates and dominant frequencies constitute all features for the damage detection.

The first question that needs to be addressed in this research where the number of recorded data is limited is to establish the number of data required to produce a reliable ANN model. If the number of training data is too small, we expect the training will not produce a good applicable model for general use. On the other side, if the number is too big, it will leave only a limited number of data for testing. In this case, the testing accuracy may be very high due to the limited variability in the testing data.

As a general guideline, the appropriate number of data for training should be able to produce a reliable model where the model performance is not affected by the data size. For this purpose, we train our ANN model by varying the number of training data from 10% up to 90% of the total data of 832 records. For each portion, Monte Carlo simulation is performed where the ANN model parameters are estimated from different random initial values.

The results are depicted in Figure 5. The results are in agreement with our anticipation. The model has low prediction accuracy when it is trained from a small size of data. However, it has high accuracy when the training data size is big. We witness, for the training data size in the range of 40% up to 60%, the model accuracy is rather reliable irrespective of the data size.

From these results, we conclude that the training data size of 50% of the total records should facilitate the development of a reliable and generally applicable ANN model. This number will be used in the following investigations.

In the present three-layer neural network model, the number of the neurons in the hidden layer is a variable that needs to be optimized. The number of neurons in the input

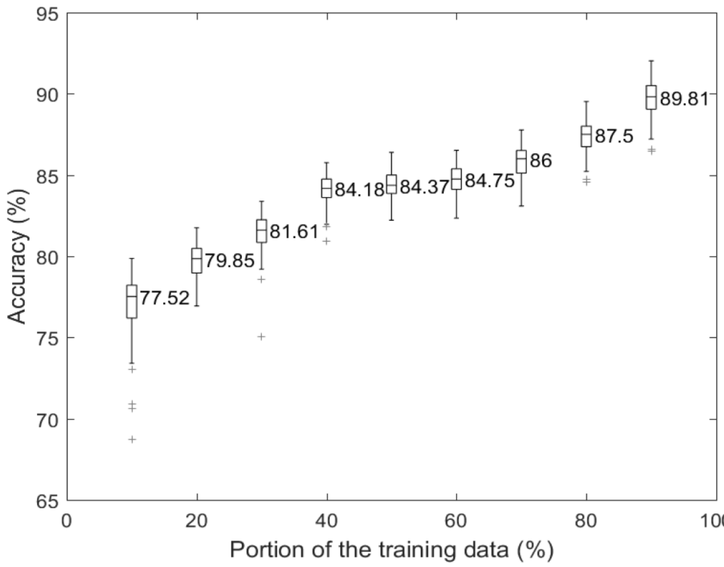


FIGURE 5. The effects of the size of the training data to the prediction accuracy in the testing phase

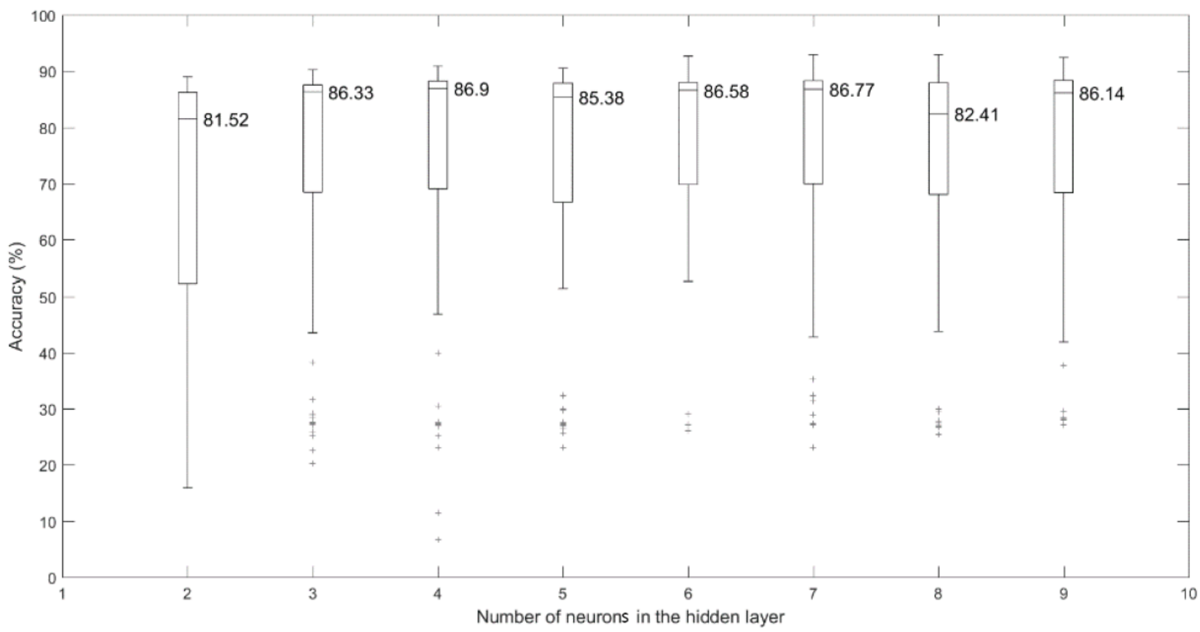


FIGURE 6. The effects of the number of neurons in the hidden layer to the classification accuracy in the testing phase

layer is fixed depending on the number of features. In the output layer, the number of neurons is also fixed.

In the search of the optimal model, we adopt the law of parsimony, which seeks for the most simple but economical model. In other words, we seek for a model that provides highest prediction accuracy and has the lowest computational cost. The problem is also solved by applying Monte Carlo simulation where the number of neurons is varied from two up to nine neurons. For each size of neurons, the model is trained for 100 times, and the model prediction accuracy is evaluated for each training. The results are depicted in Figure 6 where the accuracy of the model during the test phase is plotted against the number of neurons in the hidden layer. The figure helps us to conclude that the model having two neurons in the hidden layer is not sufficient as it has high variability in the accuracy; hence, it is less reliable.

TABLE 3. The six studied cases to reveal the most important feature

Cases	Features			
	$\dot{\theta}_x$	$\dot{\theta}_x$	f_x^{dom}	f_y^{dom}
A	×	×		
B	×	×	×	×
C		×	×	×
D	×		×	×
E	×	×		×
F	×	×	×	×

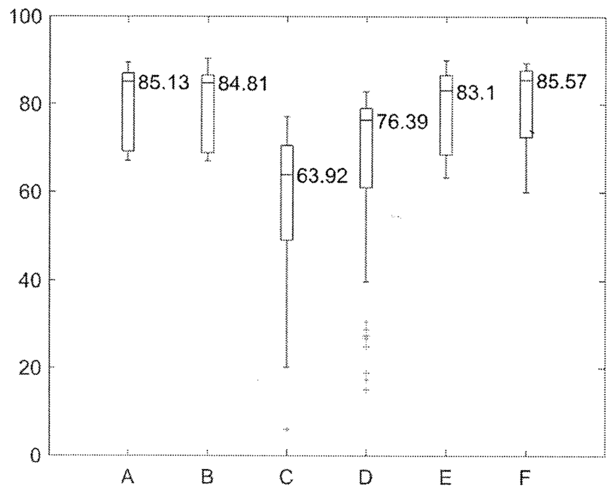


FIGURE 7. The effects of types of features to the classification accuracy. The vertical axis is the accuracy in percent. The features associated with the cases of A, B, . . . , F are provided in Table 3.

The model with three neurons seems to be the one that fits with the parsimony law: the most simplest model but sufficiently accurate. Despite its simplicity, the model accuracy is in par with those complex models with more neurons in the hidden layer.

Finally, we discuss how the features affect the classification accuracy. We only discuss four features, namely, the maximum rate of rotation in x direction or pitch rate ($\omega_x^{\max}$), the maximum rate of rotation in y direction or roll rate ($\omega_y^{\max}$), the dominant frequency associated with the pitch rate (f_x^{dom}), and the dominant frequency associated with the roll rate (f_y^{dom}). We study the combination of features as those are tabulated in Table 3. In Case A, the damage classification is performed based only on $\omega_x^{\max}$ and $\omega_y^{\max}$ features. For each case, Monte Carlo simulation is used to understand the statistical distribution of the classification accuracy.

The results presented in Figure 7 indicate the cases of A, B, E, and F tend to produce rather similar level of accuracy. This suggests that only the features of $\omega_x^{\max}$ and $\omega_y^{\max}$ are the most significant to the classification accuracy. Removing any of those features reduces the level of accuracy significantly as demonstrated by the results of the cases C and D.

4. **Conclusions.** This research article discusses the problem of automatic road-damage classification based on vehicle vibration data by using a machine learning approach. Previously, the problem was solved by using a decision tree and vehicle acceleration data

in longitudinal and lateral directions. The present approach uses a simple three-layer ANN model and vehicle rates of rotation data. This approach is able to classify the road damage at 85% accuracy. It is also found that the ANN model with three neurons on the hidden layer seems to be optimum. The contributions of the dominant frequencies to the accuracy are negligible. The maximum vehicle rates of rotations in the longitudinal and lateral directions are the determining factors on the classification accuracy.

By comparing the current results to those of [24], we see that the achieved accuracy level by using the acceleration data and that by using the rotation-rate data are rather comparable. We suspect that by combining the two types of data, a higher classification accuracy may be achieved. We leave this issue for the future work.

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