Vibration-based classification of road damages: gyroscope data and a simple neural network model

Fergyanto E. Gunawan\textsuperscript{a}, Herriyandi\textsuperscript{b}, Benfano Soewito\textsuperscript{b}, Tuga Mauritsius\textsuperscript{c}, Nico Surantha\textsuperscript{b}

\textsuperscript{a}Industrial Engineering Department, BINUS Graduate Program - Master of Industrial Engineering, Bina Nusantara University, Jakarta, Indonesia 11480

\textsuperscript{b}Computer Science Department, BINUS Graduate Program - Master of Computer Science, Bina Nusantara University, Jakarta, Indonesia 11480

\textsuperscript{c}Information Systems Management Department, BINUS Graduate Program - Master of Information Systems Management, Bina Nusantara University, Jakarta, Indonesia 11480

Corresponding author: fgunawan@binus.edu

Abstract. A system for automatic detection of road damages is essential for logistics management. At the core of the system lies an algorithm for classification of damages. This work intends to establish such an algorithm. In the current proposal, the algorithm receives data of the probe vehicle rate of rotations, extracts statistics descriptive from the data to produce a feature vector, and finally, feeds the vector to a simple-three-layer neural network to classify the damages. The types of damages are limited to four cases: normal, pothole, speed bump, and expansion joint. For the development, a probe vehicle is used to produce 400 empirical data involving those four damage cases. By using Monte Carlo approach, the established neural network model is evaluated. The results show that the approach is able to classify the cases with 85% accuracy. The study also finds that the rates of pitch and roll to be the determining factors.

1. Introduction

According to Indonesia Traffic and Transportation law [1], legislated in 2009, road administrators oblige to repair quickly any damaged roads. They may be sent to jail for five years maximum if the damaged roads result in traffic accidents. For the reason, they should continuously monitor conditions of roads. This task is hard to achieve if the monitoring is performed manually in a pervasive road network [2] in metropolitan cities such as Jakarta. An automatic road-damage monitoring system is necessary.

The need of such system is general. Many ideas have been proposed and many articles have been published. Many had proposed various detection schemes [3,4]. Articles [5,6] discussed the use of a lased-based imaging method. Articles [7,8] put forward computer vision-based techniques. Articles [9–13] asserted vibration-based methods.

The vibration-based methods have an advantage as vibration sensors such as acceleration sensor and gyroscope sensor are widely available in modern smartphones. They can be implemented by using...
low-cost mobile devices as demonstrated by Refs. [9–14]. In Ref. [12], the method was evaluated by using

a simple classification method. An Artificial Neural Network (ANN) was used in Ref. [15]. The most proposed methods [2,9,12,15] relied on acceleration sensor or accelerometer. In the current work, the system is based on gyroscope data.

Both gyroscope and accelerometer have advantages and disadvantages. Accelerometer tends to produce highly noisy data. Meanwhile, gyroscope tends to drift from the actual time when the sensor is arrested. However, since the gyroscope sensor measures the rate of vehicle rotation, we expect it to be more sensitive to road anomalies than the accelerometer sensor.

2. Research Methods

The data for the current study are collected by the following procedure. Firstly, a probe vehicle is selected (see Fig. 1). A road segment contains three road anomalies, namely, pothole, expansion joint, and speed bump, is prepared. Two smartphones are installed in the probe vehicle. The first is OnePlus One manufactured by Opo. The second is Lenovo P70 manufactured by Lenovo. The first is placed on the car dashboard. The second is on the car floor.

The probe vehicle is driven to run across the road segment at two speed settings: 3 m/s and 6 m/s. The speed is controlled by speedometer reading; thus, it is not strictly controlled. For each road anomalies, the experiment is repeated for 60 times. In addition, the vehicle vibration on normal road condition is also recorded for 60 cases.

The vehicle maximum rotation-rate in pitch, roll, and yaw are extracted from the data and a simple neural network model is established to classify the road conditions. The model specifications are presented in Table 1.

3. Results and Discussion

Firstly, we discuss how the gyroscope in the probe vehicle 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 Figs. 2–4. 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.
Figure 2. The typical recorded vehicle rates of rotations in x-, y-, and z-directions when the probe vehicle runs over a normal road condition. Those directions are related to the vehicle pitch, roll, and yaw, respectively.

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 3 shows the typical vehicle rates of rotations when the vehicle runs over a pothole. We witness as 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 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.

Table 1. The parameters and their values related to the three-layer Artificial Neural Network model in the study.

| Parameters                                      | 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.
Figure 3. The typical recorded vehicle rates of rotations in x-, y-, and z-directions when the probe vehicle runs over a road with a pothole.

Figure 4. The typical recorded vehicle rates of rotations in x-, y-, and z-directions when the probe vehicle runs over a road with a speed bump.
Figure 5. The typical recorded vehicle rates of rotations in x-, y-, and z-directions when the probe vehicle runs over a road with an expansion joint.

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        | x (Pitch) | y (Roll) | z (Yaw) |
|-----------------------|-----------|----------|---------|
| Normal                | -         | -        | -       |
| Pothole               | ×         | ××       | -       |
| Speed bump            | ×××       | -        | -       |
| Expansion joint       | ××        | x        | -       |

Now, let us shift our focus to the case of speed bump. The relevant data are presented in Fig. 4. 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 Fig. 4 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.

Next, we extract the maximum rates of rotations from each direction and used 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 [16]. The data of rates and dominant frequencies constitute all features for the damage detection.

In the search of the optimal model, we adopt the law of parsimony, which seeks for the most simple but economical model. In the 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 Fig. 6 where the accuracies of the model during the test phase are 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, so it is less reliable.

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

4. Conclusion
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 neuron on the hidden layer to be optimum. The contribution 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.

References
[1] Undang-undang republik indonesia nomor 22 tentang Lalu Lintas dan Angkutan Jalan
[2] Seraj F, van der Zwaag B J, Dilo A, Luarasi T and Havinga P 2014 Big data analytics in the social and ubiquitous context (Springer) pp 128–146
[3] Wang J, Ma S and Jiang L 2009 ICCTP 2009: Critical Issues In Transportation Systems Planning, Development, and Management pp 1–6
[4] Jog G, Koch C, Golparvar-Fard M and Brilakis I 2012 Computing in Civil Engineering (2012) pp 553–560
[5] Yu X and Salari E 2011 IEEE International Conference on Electro/Information Technology (EIT) (IEEE) pp 1–5
[6] Venkatesh S, Abhiram E, Rajarajeswari S, Kumar K S, Balakuntala S and Jagadish N 2014 Mobile Computing and Ubiquitous Networking (ICMU), 2014 Seventh International Conference on (IEEE) pp 80–80
[7] Danti A, Kulkarni J Y and Hiremath P S 2012 International Journal of Modeling and Optimization 2 658–662
[8] Huidrom L, Das L K and Sud S 2013 Procedia - Social and Behavioral Sciences 104 312–321
[9] Eriksson J, Girol L, Hall B, Newton R, Madden S and Balakrishnan H 2008 The Sixth Annual International conference on Mobile Systems, Applications and Services (MobiSys 2008) (Breckenridge, U.S.A.)
[10] Vittorio A, Rosolino V, Teresa I, Vittoria C M, Vincenzo P G et al. 2014 Procedia-Social and Behavioral Sciences 111 242–251
[11] De Zoysa K, Keppityagama C, Seneviratne G P and Shihan W 2007 Proceedings of the 2007 workshop on Networked systems for developing regions (ACM) p 9
[12] Gunawan F E, Yanfi and Soewito B 2015 International Seminar on Intelligent Technology and Its Application (ISITIA) (Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia) URL http://dx.doi.org/10.1109/ISITIA.2015.7219943
[13] Astarita V, Caruso M V, Danieli G, Festa D C, Giofr V P, Iule T and Vaiana R 2012 Procedia - Social and Behavioral Sciences 54 1135–1144
[14] Douangphachanh V and Onemaya H 2014 Informatics in Control, Automation and Robotics (ICINCO), 2014 11th International Conference on vol 1 (IEEE) pp 783–787
[15] Purnama Y and Gunawan F E 2018 TELKOMNIKA Indonesia Journal of Electrical Engineering 16 1–8
[16] Brigham E O 1974 The Fast Fourier Transform (Englewood Cliffs, New Jersey: Prentice-Hall, Inc.)