A Sound-based Machine Learning to Predict Traffic Vehicle Density

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Abstract

Traffic flow mismanagement is a significant challenge in all countries especially in crowded cities. An alternative solution is to utilize smart technologies to predict traffic flow. In this study, frequency spectrum describing traffic sound characteristics is used as an indicator to predict the next five-minute vehicle density. Sound frequency and vehicle intensity are collected during a thirteen-hour data gathering. The collected sound intensity and frequency are then used to learn three machine-learning models - support vector machine, artificial neural network, and random forest and to predict vehicle intensity. It was found out that the performances of the three models based on root-mean-square-error values are 12.97, 16.01, and 10.67, respectively. These initial and satisfactory results pave a new way to predict traffic flow based on traffic sound characteristics which may serve as a better alternative to conventional features.

Keywords: vehicle density, sound features, sound intensity, machine learning, traffic prediction, random forest, artificial neural network, support vector machine

1.0 Introduction

Traffic congestion has become a burden across the world. It is a blight on clocked-up cities and becomes a severe drain on the economy and the environment wherein about $87 billion is taken away from a country annually due to debilitated traffic flow management plans ("The City of the Future", 2016).. The Philippines is a country that ranked sixth in having a deplorable traffic flow situation in the world and ranked fourth in having the worst traffic congestion in Asia (Hegina, 2015). Moreover, Cebu was declared as the worst urban area in the world for drivers (Tan, 2016). Thus this study aims to contribute to mitigate traffic problems in Cebu by predicting short-term traffic flow using machine learning algorithms.

Several studies have already been established in anticipating traffic conditions in the next few minutes. One of which is the modeling of traffic characteristics according to Vlahogianni et al. (2014) that concerns the prediction based on current and past traffic information from a few seconds or a few hours. Another study by Kumar et al. (2015) also utilizes the use of a five-minute to thirty-minute increase in the time interval for traffic flow prediction. On top of that, short-term traffic flow prediction is vital for developing dynamic and highly efficient control of traffic management. Essential inputs for traveler information and traffic management are provided by short-term traffic flow prediction (Yang et al., 2006).

The number of vehicles per square area, also known as vehicle intensity, tends to be a good indicator due to its valuable accuracy in predicting short-term traffic flow (Litman, 2006). Different studies of short-term traffic flow prediction approaches have used various variable features or parameters such as surveillance images to determine vehicle density thus predict traffic flow (Celikoglu, 2013; Lisangan & Sumarta, 2017; Silvano & Bang, 2016; Wild, 1997). Previous study of the researchers makes use of Mask R-CNN to count and classify vehicle classes (Piedad et al., 2019). This aided the researchers in their vehicle classification collection.

Sound intensity measured in hertz or sound frequency has never been used in the literature for short-term traffic flow prediction, as far as the authors are concerned. This makes sound frequency a novel feature for predicting short-term traffic flow. There are similar studies that investigate the relationship of traffic noise or sound to the number of vehicles but not using them for predicting short-term traffic flow. A study by Halim and Abdullah (2014) shows that the heavy traffic flow on roads recorded higher noise compared to low traffic flow on roads. The roadside sound frequency shows a directly proportional relationship to vehicle intensity. However, this relationship only focuses on the noise generated by tricycles, specifically in a residential area. More accurate results were obtained if sound frequency quantification was taken in open spaces, including the sound frequency given off by other types of vehicles (Vergel et al., 2004). In this study, sound frequency serves as the feature to predict vehicle intensity for the next five minutes.

The prediction of short-term traffic flow needs analysis of data to inspect, cleanse, transform, and model data to have useful information that supports prediction and decision making. One of the core subareas of artificial intelligence is machine learning which produces accurate results and analysis by developing efficient and fast algorithms and data-driven models. This paper applies machine learning methods to develop models that can predict traffic flow in the next minutes. Several studies utilized machine-learning algorithms for better prediction results.

However, this study employs only three machine-learning algorithms that best fit to predict short-term traffic flow. These machine-learning algorithms are support vector machine, artificial neural network, and random forest. The accuracy of these prediction models is known through a performance evaluator known as the root mean square error.

Empirical implementation of predicting short-term traffic flow using sound frequency with an integrated machine learning algorithm is proposed in this study. Support vector machine, artificial neural network, and random forest were used during training and testing of datasets, and the algorithm that has the best fit was considered for predicting short-term traffic flow.

2.0 Methodology

Figure 1. *Data collection test environment with the actual camera view*

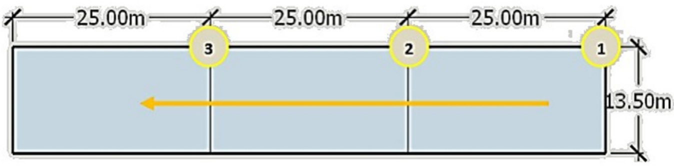

Figure 2. *One side of the road test setting of the research environment*

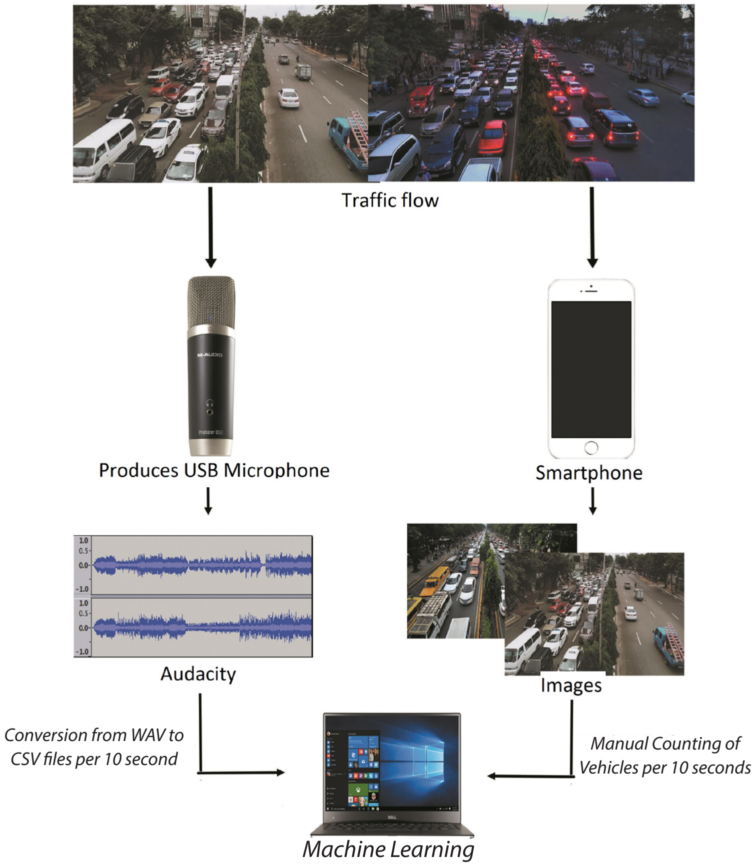

Figure 3. *Data collection flowchartt*

The locale of this study is at Osmeña Boulevard as shown in Figure 1. Specifically, the section from the first end of the waiting shed after Crown Regency Hotel up to the nearest skywalk going to Osmeña Circle was focused. The environment is 75 meters long and 13.5 meters wide as shown in Figure 2. It is considered as the major arterial thoroughfare in Cebu City for having the only road with four lanes. This indicates that this section of Osmeña Boulevard is an avenue of a busy street that is best for the nature of the study.

The sound from the other side of the road is assumed to have lower intensity and can be considered as noise. Figure 3 displays the flowchart of sound frequency data collection. The steps are elaborated as follows.

1. Setting up the equipment. Connect producer USB-connected microphone to the laptop. Producer USB microphone records the sound with the aid of an application. Prepare the smartphone for video recording of vehicles.
2. Recording. Simultaneously start the recording of sound and video of vehicles. The sampling frequency for both sound and image collection is 10 Hz. The technique in recording is similar to Caladcad et al. (2020).
3. Stop Recording. Simultaneously end the sound recording and video recording of vehicles after the target time for data collection.
4. Export and conversion. For the recording of sound, export it from the application as WAV file and convert it to a CSV file (analog to digital conversion). Then take the average the sound frequency values per ten seconds. For the recording of vehicle intensity, manually count the number of vehicles per ten seconds within the research environment. Using Fourier transform, convert the time-domain signal into a frequency spectrum similar to Chen et al. (2019) and Chang et al. (2018) studies. Fig. 4 shows the sound conversion process from sensor data to raw data.
5. Data pre-processing. Align the data for sound frequency and the data for vehicle intensity for machine learning purposes and others. There is a total of 3,000 data sampling points with a data partition of 70% and 30% for training and testing, respectively.

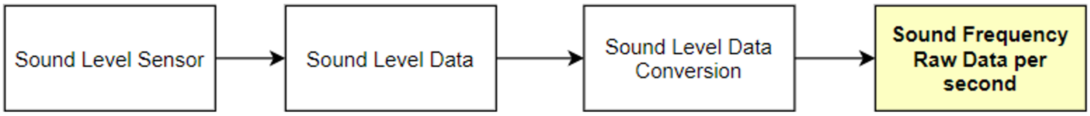

Figure 4. *The Conversion Process of Sound Frequency Data*

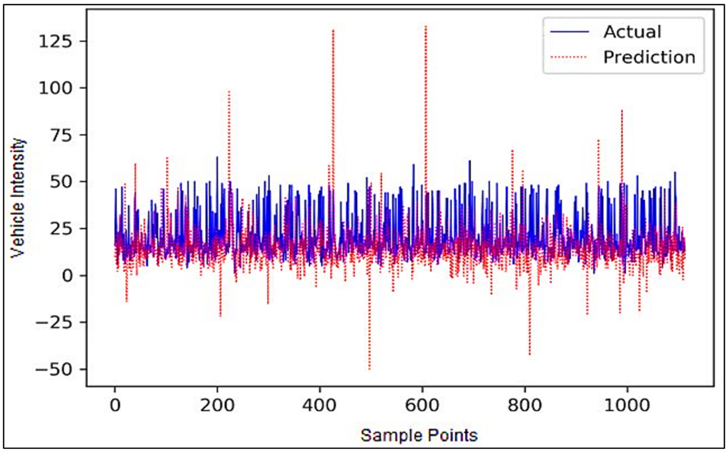

Figure 5. *Result of Support Vector Machine Regressor*

3.0 Results and Discussion

The performances of three regressor models are presented based on their root mean square error (RMSE). The lower the value of this, the better fit the prediction is.

Machine Learning

This section deals with the application of all three machine learning algorithms utilized in this study. After the data collection, the three machine learning algorithms were trained and tested upon selection of the best machine-learning algorithm (MLA) to predict short-term traffic flow are Support Vector Machine (SVM), Artificial Neural Network (ANN), and Random Forest (RF). The performance of the three machine-learning algorithms in prediction was evaluated using RMSE.

Sound data, for every five (5) minutes is fed to each model to predict the vehicle intensity in the next five (5) minutes. The difference between values predicted by the model and the values observed is called the RMSE. Figure 5 shows the testing phase of using the SVM model. The blue line represents the frequency spectrum of the actual sound signal. SVM is a supervised machine-learning algorithm that can be used for classification and regression. The testing phase of the SVM yields an RMSE value of 12.97.

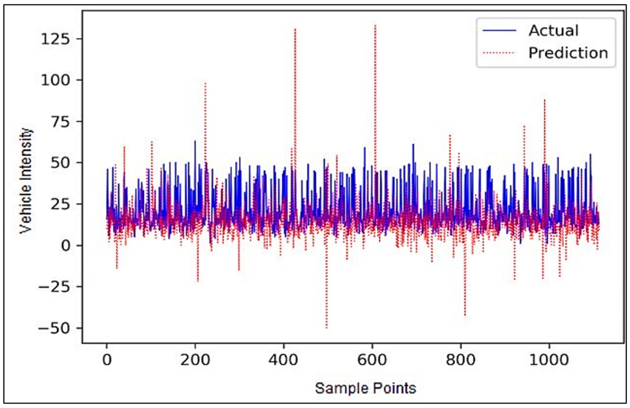

Figure 6. *Result of Artificial Neural Network Regressor*

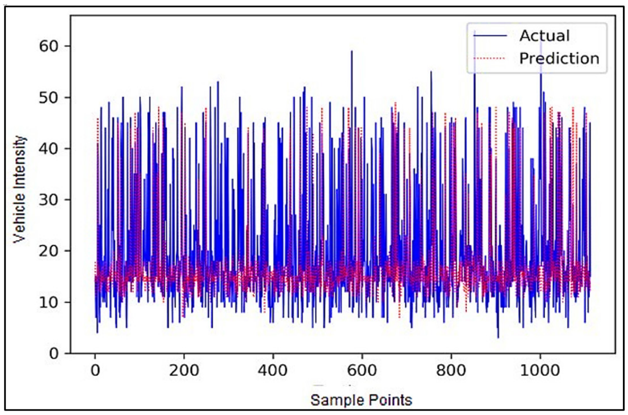

Figure 7. *Result of Random Forest Regressor*

Figure 6 shows the testing using the ANN which is a mathematical model that is inspired by biological neural networks or nodes. The testing phase of the Artificial Neural Network yields an RMSE value of 16.01. Figure 7 reflects the test using the Random Forest (RF). RF builds an ensemble or committee of decision trees that can be used to predict short-term traffic flow. The testing phase of Random Forest yields an RMSE value of 10.67.

Table 1 shows the yielded RMSE values of the three machine learning algorithms. RF yielded the least RMSE value of 10.67 and followed by SVM with an RMSE value of 12.97. Lastly, ANN yielded the highest RMSE value of 16.01. Consequently, the machine learning algorithm that yielded the least RMSE for sound frequency is Random Forest. However, to determine whether RF is indeed the best algorithm for this study, a cross-validation must take place.

Cross-Validation

In the cross-validation process, the data set was shuffled to create new training and testing data sets. The performance of the random forest was validated whether it was consistent or not. If the performance were consistent, then the model would be considered the best machine-learning algorithm to predict short-term traffic flow. Each machine-learning algorithm underwent cross-validation for ten times wherein each algorithm was trained and tested as shown in Table 2. Random Forest has a consistent performance wherein it yielded the lowest RMSE among the three algorithms throughout the tenth-fold cross-validation. Moreover, by averaging, SVM ranks second while ANN ranks last. The results in cross-validation are the same as the results in the first learning phase. Hence, it can be validated that Random Forest (RF) is the best machine-learning algorithm to predict short-term traffic flow.

Table 1. *Performances of the Three Models*

Root Mean Square Error (RMSE)	**F1-score**		
	SVM	***ANN***	***RF***
	12.97	16.01	10.67

Table 2. *A Ten-fold Cross-Validation*

Sample Frequency	**F1-score**		
	SVM	***ANN***	***RF***
1	13.00	19.19	11.14
2	11.95	15.04	10.42
3	12.22	19.61	10.15
4	12.12	17.93	10.48
5	13.34	22.14	11.33
6	12.48	16.67	11.18
7	11.99	18.15	11.11
8	12.41	16.74	10.52
9	10.27	15.73	10.52
10	12.08	14.02	10.43
Average	**12.19**	**17.52**	**10.73**
Rank	**2**	**3**	**1**

All machine-learning models used in this study are black-box models. The models are difficult to uncover any perceivable relationship within the process but their processes can be demonstrated mathematically. However, in literature, each model performs differently depending on the kind of application. And in this case, RF had the best performance of all.

4.0 Conclusion

A novel way of predicting short-term traffic flow is developed using sound intensity and its features. The Random Forest model yielded the least RMSE values among the three algorithms. Support vector machines and neural networks still performed satisfactorily. This study is still in its first stage and better results are expected in the future. Other techniques like deep learning can be used in the future.

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