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# VEHICLE DETECTION AND CLASSIFICATION USING FORWARD SCATTER RADAR (FSR) FOR TRAFFIC MANAGEMENT USING CONVOLUTIONAL NEURAL NETWORK

**N. N. Ismail[1], N. E. A. Rashid[2], M. N. F. Nasarudin[3], W.M. W. Mohamed[4], S. Zainuddin[5], Z. I. Khan[6]**

[1,2,6]*Microwave Research Institute,*
UNIVERSITI TEKNOLOGI MARA, SHAH ALAM, MALAYSIA
[3]*School of Electrical Engineering, College of Engineering,*
UNIVERSITI TEKNOLOGI MARA, SHAH ALAM, MALAYSIA
[4]*Malaysia Institute of Transport (MITRANS),*
UNIVERSITI TEKNOLOGI MARA, SHAH ALAM, MALAYSIA
[5]*Faculty of Electrical and Electronic Engineering Technology,*
UNIVERSITI TEKNIKAL MALAYSIA, MELAKA

## Abstract

The importance of automatic vehicle detection and classification has grown significantly in recent years, as it has become a crucial component of traffic management and monitoring systems. To overcome the limitations of traditional video vehicle detection, this paper proposes the use of forward scatter radar (FSR) technology. The FSR system is tested for the classification of four different vehicle types, each with distinct sizes. To improve the classification accuracy of the FSR system, the paper utilizes a well-established neural network known as a convolutional neural network (CNN). Two time-frequency analyses, continuous wavelet transform (CWT) and short-time Fourier transform (STFT), are used to evaluate the classification performance of the FSR system. The study demonstrates that the CNN classifier significantly improves the classification accuracy of the FSR system in vehicle detection and classification. This finding is supported by the evaluation of the time-frequency analyses, CWT and STFT. Overall, the proposed approach has the potential to enhance traffic management and monitoring systems, thereby improving road safety and traffic efficiency.

***Keywords:*** Vehicle Classification, Forward Scatter Radar (FSR), Convolutional Neural Network (CNN), Continuous Wavelet Transform (CWT), Short-time Fourier Transform (STFT)

[2] Assoc. Prof. Ir. Dr. at UiTM. Email: emileen98@uitm.edu.my

## INTRODUCTION

Vehicle detection and classification technologies are crucial in various civilian and military applications, including transportation planning and highway traffic monitoring (Abdul Ghapar Othman & Kausar Hj Ali,2020). Formerly, vehicle identification, segmentation, and tracking technologies were utilized to compute the fee for different types of vehicles for the automated toll levy system using a vision-based supervision system (Lai, Fung, & Yung, 2001)( Nahry Yusuf, 2018). Recently, researchers have used the vehicle recognition system in detecting vehicles or traffic lanes (Lim, Ang, Seng, & Chin, 2009)(Gomaa, Minematsu, Abdelwahab, Abo-Zahhad, & Taniguchi, 2022). The system has also been used in classifying various vehicle types on roads such as automobiles, motorcycles, vans, and busses, to name a few (Kato, Ninomiya, & Masaki, 2002)(Chetouane, Mabrouk, Jemili, & Mosbah, 2022)(Ahmed et al., 2023).

Nevertheless, the success of the system is contingent on excellent traffic image processing methodologies to detect and classify the vehicles, which may be hindered when the vehicles are obscured by other vehicles or by background barriers. Furthermore, the system is also susceptible to unfavorable weather conditions and its efficacy degrades in severe situations such as rain, snow, and fog (Bijelic, Gruber, & Ritter, 2018). As a result of those constraints, researchers have begun to explore alternative methods for the past few years besides the vision-based system. One of the reliable systems that are more resilient under weather circumstances is a radar system (Müller, 2017), which has been found in widespread use in autonomous vehicle systems (Caesar et al., 2020)(Bijelic et al., 2020).

Forward scattering radar (FSR), a specialized kind of bistatic radar with a detection angle of 180°, has been studied extensively in recent years in detecting and classifying ground targets, including humans and vehicles (N. E. A. Rashid et al., 2008)(Gashinova, Sizov, Zakaria, & Cherniakov, 2010)(Hafizah Abdul Aziz & Firdaus Hussain, 2020)(Nur Emileen Abd Rashid et al., 2021)(Mamat & Aziz, 2022) due to its number of peculiarities, especially robust to stealth technology (Hiatt, Siegel, & Weil, 1960). Classification of FSR ground targets has been studied since at least 2005 (Cherniakov, Raja Abdullah, Jančovič, & Salous, 2005). In the study, principal component analysis (PCA) is utilized as an automated feature extraction method, and the suggested FSR system uses solely k-nearest neighbor (KNN) as its classifier. The combination techniques have also been utilized in (R. S. A. R. Abdullah & Ismail, 2006)(R. S. A. R. Abdullah, Saripan, & Cherniakov, 2007)(Raja Abdullah, Abdul Aziz, Abdul Rashid, Salah, & Hashim, 2016)(Aziz, Hadi, Rahman, Alias, & Al-Hiealy, 2022), where the combination produces an excellent classification performance, which offers an accuracy of greater than 90%. In (Nur Fadhilah Abdullah, Rashid, Musirin, & Khan, 2015), the authors utilized the PCA and Z-score for the feature extraction process in the FSR system to investigate which feature extraction technique would be the most effective when it comes to classifying ground vehicles. The work continued in (Nur Fadhilah Abdullah, Rashid, Othman, Khan, & Musirin, 2017)(N. F. Abdullah, Rashid, Ibrahim, & Abdullah, 2017) as the authors developed more methods for enhancing classification accuracy by using the combination of Z-score and neural network (NN), where it was found that the combination provides an excellent classification pattern. An artificial neural network (ANN) technique called feed-forward back-propagation (MPL) architecture is used in (Ibrahim, Abdullah, & Saripan, 2009)(M., Kanona, & Elsid, 2014) for classifying the FSR target signal. At the end of the study, the ANN provides a greater rate of accurate classification than the KNN classifier.

In recent years, a convolutional neural network (CNN) has seen widespread use in the vehicle classification process vehicleried out by radar systems (Zhang, Xu, & Li, 2022)(Saranya, Archana, Reshma, Sangeetha, & Varalakshmi, 2022)(Garcia, Aouto, Lee, & Kim, 2022). This is due to the fact that CNN is able to automatically recognize important characteristics without the need for any kind of human intervention compared to its predecessors (Gu et al., 2018). In order to explore its potential applications, in this study, the CNN classifier is proposed in vehicle classification for the FSR system, and to the best of the authors' knowledge, this is the first time that the CNN classifier is demonstrated to the FSR system. Two types of time-frequency analysis are applied in this study to evaluate the classification accuracy, which are continuous wavelet transform (CWT) to create a scalogram and short-time Fourier transform (STFT) to create a spectrogram. An AlexNet architecture with eight layers and an Adam optimizer with a 0.0001 initial learning rate are implemented in this study.

## RESEARCH METHODOLOGY

### Data Collection

In this study, a pair of sensors comprising a transmitter and a receiver with operating frequencies of 64, 151, and 434 MHz are employed for transmitting and receiving. The sensors are placed facing each other, forming an FSR configuration, with a separation distance of 50 m. The data are gathered on a parking lot devoid of foliage in order to acquire the least amount of muddled information. The signal transmitted from the transmitter is a continuous wave (CW) signal and the receiver will capture the signatures of four different vehicles moving one at a time perpendicularly in the middle of the baseline between the transmitter and the receiver at a constant pace of roughly 10 km/h. In order to guarantee that the signals are reliable, the measurement of each vehicle is vehicleried out 40 times, with 20 s passing between each set of data. Table 1 provides a tabular overview of the vehicles' dimensions.


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**Table 1:** Vehicle Dimensions

| Vehicle | Dimensions (height (m) x length (m)) |
|---|---|
| A | 4.8 x 2.1 |
| B | 4.5 x 1.4 |
| C | 4.4 x 1.5 |
| D | 4.0 x 1.4 |

### Data Signal Processing

The collected data consists comes in the form of three Doppler channels, each of which represents a different operating frequency, ranging from 64 to 151 to 434 MHz. The signals are captured with a frequency sampling rate, *fs* of 20 Hz over a period, *d* of 20 s. The gathered signals are filtered with a low-pass filter at a cut-off frequency of 60 Hz before being subjected to further processing. Two time-frequency analyses are applied, namely CWT and STFT to the data to create a scalogram and spectrogram, respectively. A Gaussian window size of 0.5 s and a number of overlaps of 0.4 s are applied as the parameters of the STFT. The training-to-testing ratio across all courses is 80:20. An AlexNet architecture with eight layers is utilized for the image classification task with an Adam optimizer. The learning rate is set to 0.0001 with a minibatch size of 512.

**Table 2:** Signal Processing Algorithm

| | | |
|---|---|---|
| | | **Signal initialization** |
| **1** | i. | Sampling frequency, *fs* = 20 Hz. |
| | ii. | Duration, *d* = 20 s. |
| | iii. | 3 frequencies: 64, 151, and 434 MHz. |
| | | **Filtering and time-frequency analysis** |
| **2** | i. | Apply a low-pass filter with 60 Hz. |
| | ii. | Apply CWT to create a scalogram. |
| | iii. | Apply STFT to create a spectrogram with a Gaussian window size of 0.5 s and overlaps of 0.4 s. |
| | | **Data classification** |
| **3** | i. | Divide data with a ratio of 80:20 for training and testing. |
| | ii. | Apply AlexNet architecture with 8 layers, as well as an Adam optimizer, 0.0001 initial learning rate, and 512 minibatch size. |
| | iii. | Classification percentage accuracy. |

## EXPERIMENTAL RESULTS AND DISCUSSIONS

The four vehicles' Doppler signatures captured with the operating frequency of 64 MHz are represented in Figure 1. Vehicle A which comprises a bigger size than the other three vehicles produces more signatures as can be seen in Figure 1(a). Vehicle B in Figure 1(b) generates a similar Doppler signature as vehicle A, however with a lesser amplitude as vehicle B is smaller than vehicle A. On the other hand, vehicles (c) C and (d) D produce different Doppler signatures. On the basis of the data, it is shown that the FSR system is capable of capturing various kinds of vehicles since the target Doppler signature created by the system is distinct from one another.

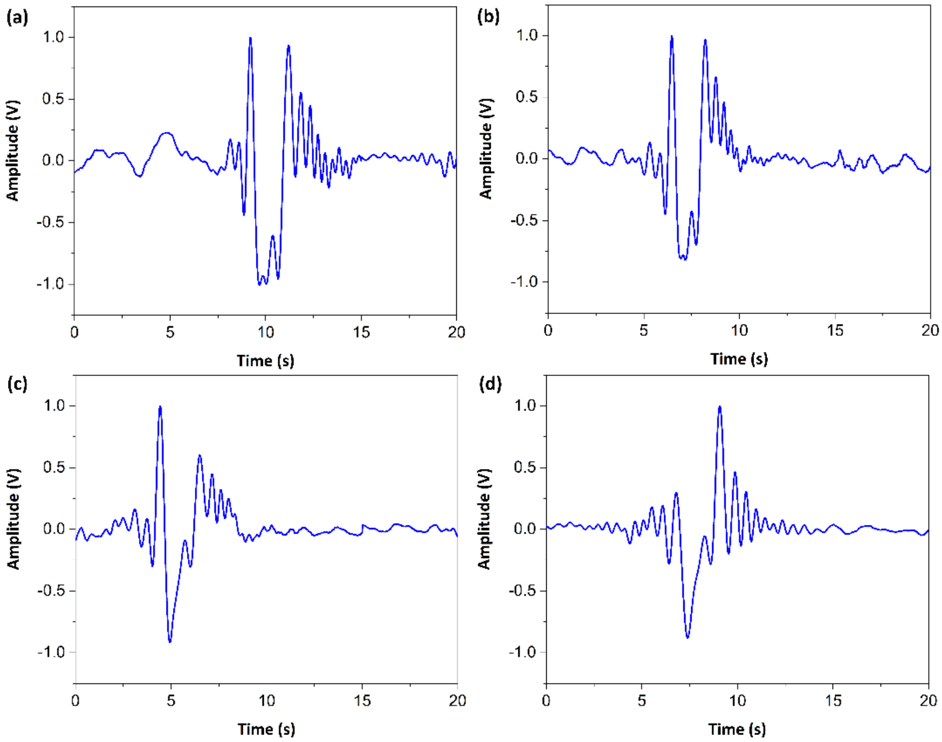


**Figure 1:** Target Doppler signature with 64 MHz operating frequency for vehicle (a) A, (b) B, (c) C, and (d) D

The clearer differences in vehicle signatures for all four vehicles, A, B, C, and D, are expressed in the frequency domain signal for the first 1.5 Hz with normalized to 0 dB as depicted in Figure 2 with the operating frequency of (a) 64 MHz, (b) 151 MHz, and (c) 434 MHz. From the figures, the difference can be seen in the main and side lobes of the target signature. Each vehicle generates a unique signature for each frequency at which it operates, which suggests that various targets will each create their unique signature.


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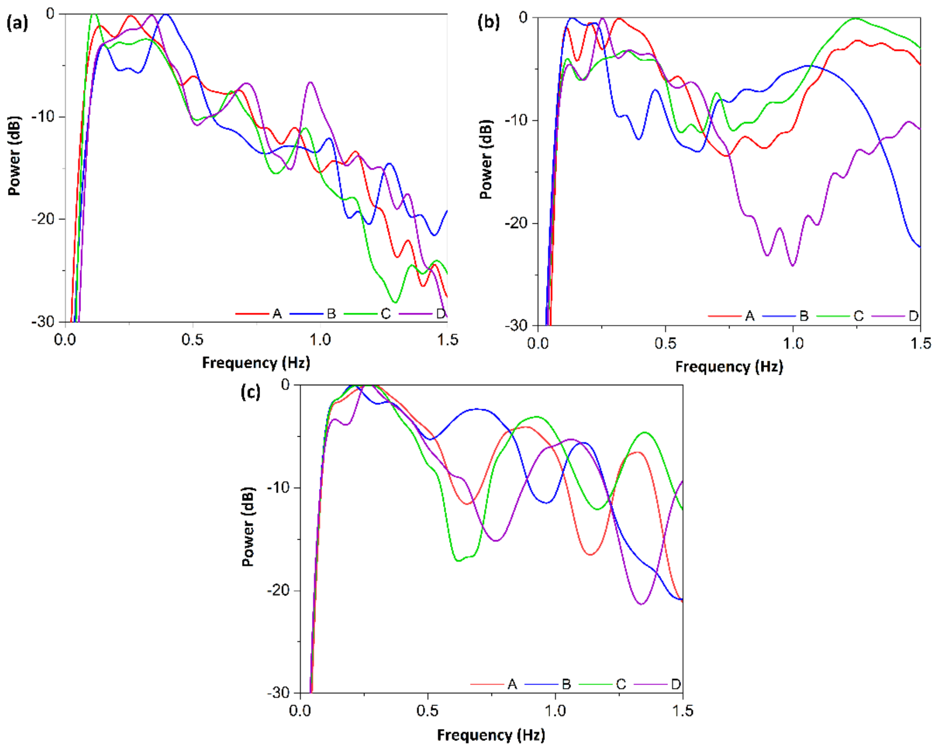


**Figure 2:** Spectra for vehicles A, B, C, and D with the operating frequency of (a) 64 MHz, (b) 151 MHz, and (c) 434 MHz

Figure 3 compares the source image with the image of the scalogram and spectrogram of the vehicle (a)(b) A, (c)(d) B, (c)(d) C, and (e)(f) D, respectively, with an operating frequency of 434 MHz. From the figure, it can be seen that the representation of the heat map between the scalogram and spectrogram is different. The spectrogram represents more intensities than the scalogram. This is because the spectrogram heat map offers more comprehensive information about the strength of the signal inside each frequency bin, but the scalogram heat map provides more detailed information about the distribution of frequencies over time. In every single composited picture, the four vehicles can be distinguished from the other by a substantial and obvious visual gap that exists between them. The brighter intensities (warmer colors) in the figures represent the crossing vehicles to the baseline of the transmitter and receiver, which reflects the Doppler signature in Figure 1. The heat map for vehicle A in both the scalogram (Figure 3(a)) and spectrogram (Figure 3(b)) is expected to be clearer because of the presence of energy due to a bigger dimension size compared to the other three vehicles.

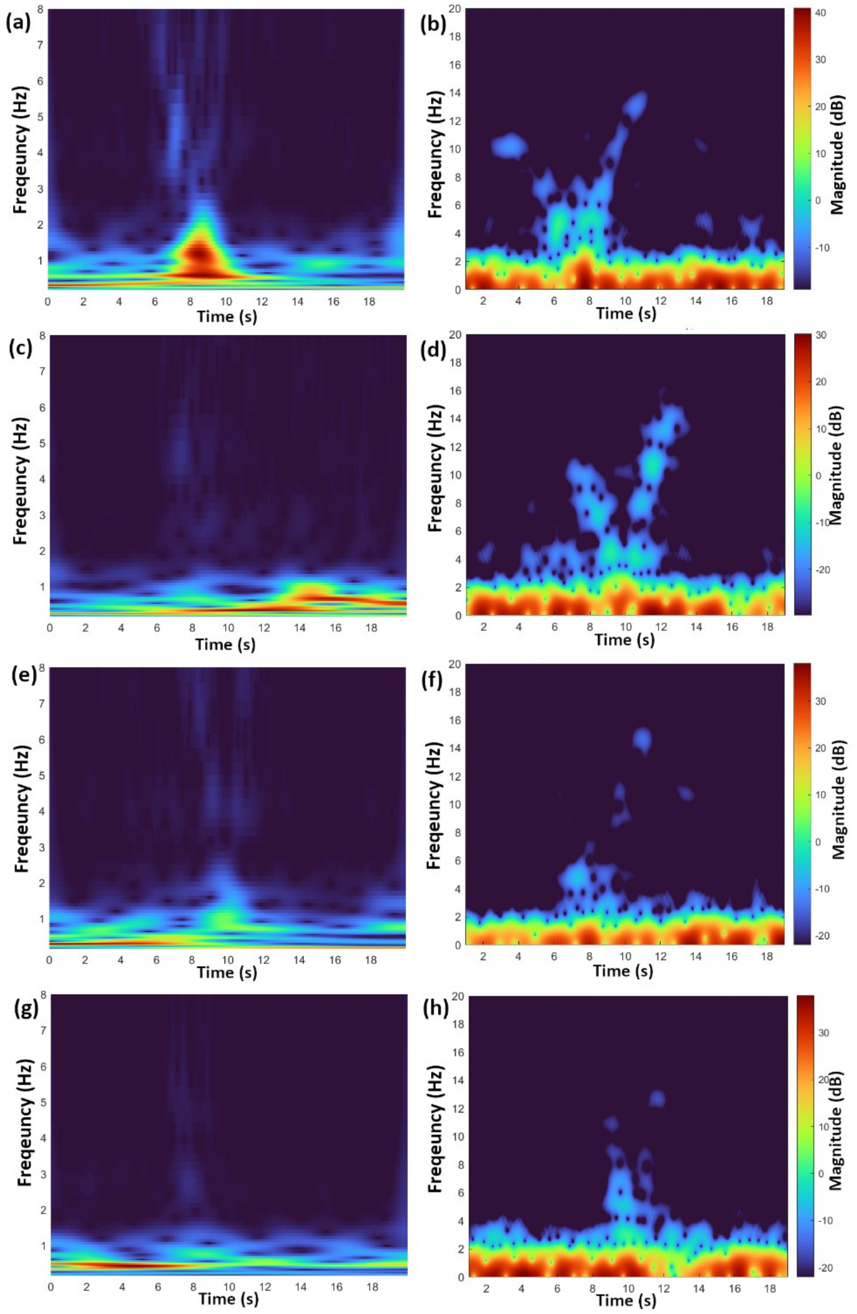


**Figure 3:** Scalogram and spectrogram of the vehicle (a)(b) A, (c)(d) B,(c)(d) C, and (e)(f) D, respectively, with an operating frequency of 434 MHz


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The classification percentage accuracy with scalogram and spectrogram techniques for 64, 151, and 434 MHz operating frequencies are tabulated in Tables 3, 4, and 5, respectively. In Table 3, only vehicle D is misclassified with a classification accuracy of 97.5% for the scalogram technique, while only vehicle C is misclassified with a classification accuracy of 95.0% for the spectrogram technique. The classifier with an operating frequency of 64 MHz has an overall accuracy of 99.4% and 98.8% for the scalogram and spectrogram techniques, respectively. However, there is no misclassification occurs using the scalogram technique for operating frequencies of 151 and 434 MHz as shown in Tables 4 and 5, respectively, resulting in an overall classification accuracy of 100%. On the other hand, there is only one vehicle that is misclassified for the operating frequency of 151 MHz using the spectrogram technique, which is vehicle B with a classification accuracy of 97.5%. The same classification accuracy of 97.5% also occurs for the operating frequency of 434 MHz with the spectrogram technique, which occurred by vehicle A. This yields an overall classification accuracy of 99.4% for both 151 and 434 MHz operating frequencies. Overall, classification accuracy with the scalogram technique produces a higher percentage than the spectrogram techniques for all three operating frequencies. Based on the classification accuracy from both types of techniques, this indicates that the CNN classifier is suitable to perform vehicle classification in the FSR system.

**Table 3** Classification percentage accuracy for 64 MHz

| **Vehicle** | **Accuracy (%)** | |
|---|---|---|
| | **Scalogram** | **Spectrogram** |
| A | 100 | 100 |
| B | 100 | 100 |
| C | 100 | 95.0 |
| D | 97.5 | 100 |
| **Overall** | **99.4** | **98.8** |

**Table 4** Classification percentage accuracy for 151 MHz

| **Vehicle** | **Accuracy (%)** | |
|---|---|---|
| | **Scalogram** | **Spectrogram** |
| A | 100 | 100 |
| B | 100 | 97.5 |
| C | 100 | 100 |
| D | 100 | 100 |
| **Overall** | **100** | **99.4** |

**Table 5** Classification percentage accuracy for 434 MHz

| Vehicle | Accuracy (%) | |
|---|---|---|
| | **Scalogram** | **Spectrogram** |
| A | 100 | 97.5 |
| B | 100 | 100 |
| C | 100 | 100 |
| D | 100 | 100 |
| **Overall** | **100** | **99.4** |

## CONCLUSION

The study utilized a CNN classifier that incorporated both scalogram and spectrogram techniques to classify four types of vehicles. These vehicles were captured by an FSR system that operated at three different frequencies: 64, 151, and 434 MHz. Based on the results obtained, it can be concluded that the CNN classifier is capable of accurately classifying vehicles when used in conjunction with the FSR system. This finding has significant implications for traffic management and monitoring systems in real time.

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