Monitoring Alignment of Automotive Radar Sensor Using RAD-Convolutional Neural Network

Sheriff Murtala, Ingyu Lee, Soojung Hur, and Yongwan Park*
Information and Communication Engineering
Yeungnam University

sheriffm@yu.ac.kr, inleeatyu@yu.ac.kr, sjheo@yu.ac.kr, and ywpark@yu.ac.kr*

Abstract

The operation of automotive radar for automated driving is safe and reliable when the orientation of the radar's position is correctly aligned with the body of a vehicle. However, when there is a misalignment in the orientation of the radar due to shocks and vibration, this affects its perception of targets in the surrounding environment. Therefore, it is necessary to monitor the alignment status of automotive radar not only during first-time installation but regularly. Recently, the convolutional neural network based on the range-Doppler map (RD-CNN) was successfully applied to monitor the alignment state of radar, but when more alignment angles are considered, the classification accuracy of the model reduces. To address this problem, more information is extracted from the radar signals and provided to the CNN. In this paper, we additionally extract the range-azimuth (RA) map images, and together with the RD map images, a RAD-CNN model that accepts two input images is trained to monitor the alignment state of radar sensors. RAD-CNN, when compared with RD-CNN, performed better with classification accuracy margin over 10%.

Ⅰ. Introduction and Background

Radar sensors for advanced driving assistance systems (ADAS) and automated driving are usually mounted behind the vehicle's bumper. The mounted radar sensor suffers from shock and vibration due to external factors [1] thereby resulting in some deviation in the orientation of the radar sensor. The misalignment of radar sensors consequently affects the decision and control operation of the vehicle.

[2] introduced a misalignment detection method based on a convolutional neural network (CNN). The neural network was trained using the range-Doppler (RD) map of reflected signals received by a tilted radar sensor. The authors considered the ground as the target (reflective surface) and the range was less than 1 m. The RD-CNN detector performance was superior to machine learning-based tilted angle detection models [3].

One of the drawbacks of the RD-CNN method is that its performance reduces when more alignment angles are considered. As a result, this paper addressed this limitation by extending the classification labels from 9 to 19 alignment angle labels. This extension reduces the classification accuracy of the RD-CNN, but with more information available to the model, the performance of the model can be enhanced. Therefore, this paper presented a two-input CNN-based classification model that accepts RD and range-azimuth (RA) map images for monitoring the alignment state of automotive radar. The block representation of the range-azimuth-doppler CNN (RAD-CNN) model structure and the procedures for the classification task are shown in Figure 1.

Ⅱ. Method & Result

Simulation Environment:

The frequency modulated continuous waveform (FMCW) radar raw signal interface (RSI) setup in Carmaker [4] was used in this paper to generate synthetic RD and RA map images. The radar is placed behind the bumper, 0.6 m high above ground. The parameters for the radar used are presented in Table 1. A stationary car target is placed at 1 m, 2 m, or 3 m in front of the ego vehicle with alignment angles ranging from −45° to 45° with intervals of 5° (19 angle labels). An example of a car at 3 m in front of the radar is shown in Figure 2.

The simulation time is 6 seconds in a scenario and 99 frames of radar RSI were collected. 2D-discrete time fast Fourier transform (FFT) was applied to each radar RSI to determine the RD map, and another 2D-discrete time FFT is applied to estimate the RA map.

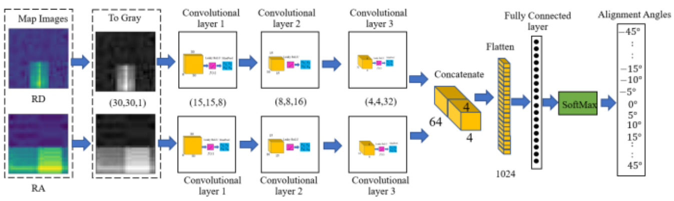

Figure 1. Block representation of the RAD-CNN model. The kernel size in each convolutional layer is 3×3, and the output sizes after 2×2 max pooling (blue) of the first, second, and third layers are (15,15,8), (8,8,16), and (4,4,32) respectively.

To reduce trainable parameters needed during the training of the CNN model, the RD map is cropped to range values from 0 to 10 m, and Doppler values from −15 to +15 m/s, and the corresponding image size is 30 by 30 pixels. Similarly, the RA is cropped to azimuth values from −15 to 15°, and range values from 0 to 10 m, the corresponding image size is the same as the RD map image.

RAD-CNN:

The proposed CNN architecture takes two images as inputs and uses two parallel branches of convolutional layers. In each branch, there are three convolutional layers, with max pooling and leaky rectified linear unit (ReLU) activation applied after each convolution operation. As shown in Figure 1, the outputs of the third convolutional layer are concatenated, flattened, and passed to the fully connected (FC) block, where we used the SoftMax to normalize the output of the network to a probability distribution over the alignment angles. The Adam optimizer with a learning rate of 0.001 was also used. With a batch size of 1, the network was trained and verified using 100 epochs.

Result & Discussion:

A total of 57 (3 different distance values and 19 different alignment angles) scenarios are considered in this paper. In each scenario, 99 radar RSI Frames were collected, and their corresponding RD and RA maps were determined. In total, 5643 RA and RD map images were generated. The data was split into 80% for training, 10% for validation, and 10% for test. We ensured that the labels were distributed uniformly in each data division. The performance of the RA-CNN and RAD-CNN are compared in Table 2.

For fair comparison of the two models, we also generated 891 RD and RA map images for 9 angle labels, same as in [2]. The breakdown is as follows; 1 (1m distance value) × 9 (alignment angles) × 99 frames data. As shown in Table 2, the performance of the RAD-CNN is better than that of RD-CNN, with accuracy over 10% in the test data for both 9 and 19 angle labels. This indicates that RAD-CNN contains rich features extracted from the RA map images, and this compensates for its probability of classifying the alignment angles correctly.

Table 1. Specification of FMCW radar used.

Parameter	Values	Parameter	Values
Transmit Freq.	77 GHz	Range Samples	256
Transmit Power	20 dBm	Doppler Samples	128
System Losses	0 dB	Angle Samples	16
Cycle time	60 ms	Range (min)	0.1m
FOV(azimuth)	30°	Range (max)	200 m
FOV(elevation)	10°		

Ⅲ. Conclusion

The alignment of automotive radar sensors is important for the accurate detection of targets in the environment. The existing CNN method based on RD map images has been demonstrated to monitor the alignment of the radar installations. However, for detecting alignment angles of the radar ranging from −45° to 45° (with 5° intervals), the classification accuracy reduces. In this paper, we proposed a method that combines the RD and RA to improve the classification accuracy of the CNN-based method for detecting the alignment of radar installation.

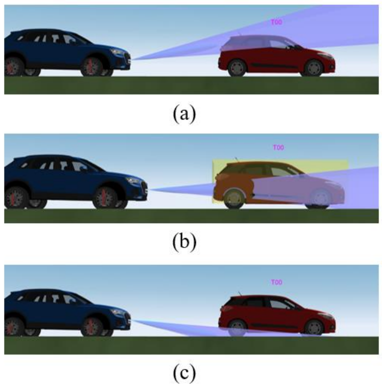

Figure 2. Radar Aligned at (a) 10° (b) 0° (c) −10° (upward/normal/downward direction).

Table 2. Performance of RD-CNN and RAD-CNN

Metrics		Models	
		RD-CNN[2]	RAD-CNN
19 Angle labels			
Loss	Training	0.340	0.300
	Validation	0.609	0.317
Accuracy (%)	Training	83.94	86.35
	Validation	77.36	87.79
	Test	73.68	84.21
9 Angle labels			
Loss	Training	0.024	0.00094
	Validation	0.0116	0.02013
Accuracy (%)	Training	99.10	100.00
	Validation	100	98.77
	Test	88	98.8

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