Camera Assisted Radar RCS Signal Fault Detection Using CNN

Dian Ning, Dong Seog Han

Graduate School of Electronic and Electrical Engineering

Kyungpook National University

Daegu, Republic of Korea

ningdian@knu.ac.kr, dshan@knu.ac.kr

***Abstract*—Self-driving usually relies on radar signals to recognize pedestrians and vehicles, identify the surrounding environment reliably, avoid car crashes and navigation, and provide a reliable route to avoid collisions. Undoubtedly, the radar plays an important role in vehicle systems. However, Sensor faults are unavoidable. When the radar sensor is faulty, the radar signal will not receive the correct feedback information. Currently, It is hard for the radar to detect faulty errors, and the algorithm is complicated to work with. We analyzed the radar cross section (RCS) signal and distance relationship. We used the RCS signal feature and combined the real-time features of the vehicle camera with the convolutional neural network (CNN) model to identify the fault information as expected. The paper uses a new data generator feature and a deep learning model to recognize the input signal as normal and abnormal with an improvement accuracy to 95.54%.**

***Index Terms*—Fault detection, Radar, RCS, CNN**

I. Introduction

Currently, with the development of science and technology, we will not just be confirming the accuracy of sensors but also their stabilises. The radar has many potential performance issues such as delay latency or time delay estimation (TDE) or may not even give the correct output signal. All of the sensors have similar problems. Sensor faults are divided into internal malfunctions (ex. mounting issues) and disturbing (like security attacks). As the definition of the faulty classification, we classified the sensor fault as a defect subcomponent, mechanical damage to sensor cover, layer on the sensor, mounting issue, security attack, unfavourable environmental condition, and crosstalk [1] as in Fig. 1.

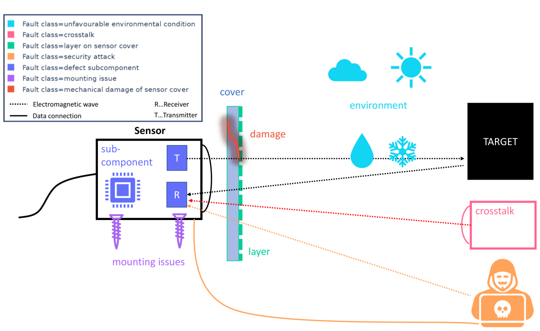


Fig. 1. Schematic illustration of sensor fault classes.

All fault classifications suffer from the output signal. We use physical methods to detect fault problems, such as voltage amplitude detection, level detection and continuous pulse detection. The physical method uses the A/D digital quantization to compare with the present threshold [2].

Researchers use a different method to detect sensor fault problems. The physical methods have many problems such as the long test time, high cost and operational complexities. Even if the methods are suitable for a sensor device, they may not have a good generalization ability for similar sensors, and they require large amounts of human intervention. Use of convolutional neural network (CNN) is a good way to improve on these disadvantages. In the fault detection area of the camera sensor, this deep learning technology has been applied in a wide range of products to improve the sensor's accuracy. The radar output is the state of the sensor, and if the output signals leave normal values with time, we recognize that the signals are at fault. We need to ensure that CNN recognizes the differentiation between normal and fault signals. Using this method, we can improve efficiency and save manpower resources by effectively shortening the debugging period.

The radar cross section (RCS) signal wave is relevant to the vehicles' appearance, the detected angle and interval distance between each vehicle. In order to get these pieces of information, we used a camera to catch the real-time images and train with the radar signal in the CNN model.

II. Dataset Collection

This dataset was collected on the KNU campus with equipment from Continental SRR 208-21 radar, which is a 24 GHz short range radar. The radar equipment values range from -50 to 30 dBm^2. At the same time, web camera was aimed to take the front of the vehicle image from the direction of the radar beam. The radar sensor and camera were placed in front of the test vehicle's rear with the same horizon level. When the test vehicle advanced and was further away from the vehicle, the radar RCS data would be collected from 5m to 50m distances.

This dataset consists of RCS data on the three angles of the vehicle, front, sides and rear. In the actual test, the Radar sensor can detect many targets at the same time. We recorded the center front vehicle target to analyze the RCS signal. Meanwhile, the camera takes photos of the tested vehicle. The test environment is as shown in Fig. 2. We collected front side (0°) data, side angle (90°) data and Back angle (180°) data, and their distance begins at $10m$ and ends at 50 m. The time series dataset, the obtained car's radar RCS and distance dataset leads $(time, dis, rcs)$ are contained in the.csv file and its real-time images.

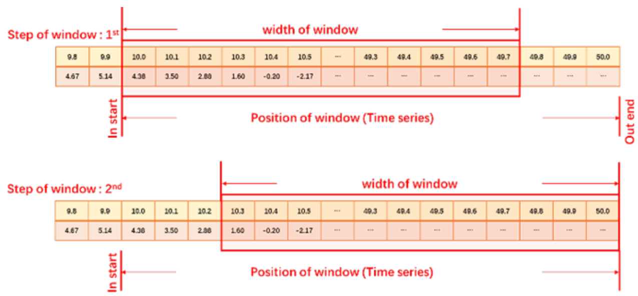


Fig. 2. Schematic illustration of sensor fault classes.

With noise transaction preprocessing, we get clear signals for the training dataset via the csv format and its real-time images. The csv format recorded every target's distance and RCS information (dis, rcs). At every instant, the RCS value will vary with the distance, so we used (x, y) to represent the relationship between the independent and dependent variables. The real-time images are color images with 224 × 224 image sizes. We used the sliding window to get the RCS signal as a sequence, with 10 steps between each window. As Fig. 2 shows, the red box, or the sliding window, is a radar RCS sequence with a size of (100, 2) which means it has 100 points of (x, y) data. The collected data is labeled normal, and we use the data generator to create the abnormal data. For each real-time image, the abnormal RCS signal is randomly set as the $(dis, rcs+noisy)$ or $(dis, rcs-noisy)$. The noise variable in the signal is normally set between 5 and 7. The yellow lines show the collected data from the same vehicle with similar angle information, and the red line is the abnormal data that has been generated.

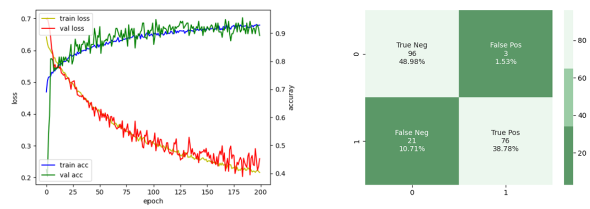
Each of the vehicles with the same viewing angle has the same RCS signal range when the distance changes. Our generator will use the extra input to generate the abnormal data and after the generation, our model input still has an RCS signal array and real-time image array. The abnormal generated is outside the normal range and can add noise, such as the Additive White Gaussian Noise (AWGN) signal.

III. Proposed Model

We hope to use the camera to assist the model more exactly. As we know, images captured by the camera are widely used for class classification. Our model is a two-branch network, with one branch identifying whether the RCS signal is normal or abnormal and the other is devoted to modelling the vehicle image. The radar branch consists of three CONV 1D layers respectively each layer followed by a MaxPooling 1D layer and we use ReLU as the activation function throughout the network. The output of the branch has signal information output by the dense layer with a size of 100. The camera branch uses a CONV 2D layer and a MaxPooling 2D layer to extract images featuring distance, vehicle type and angle information. The output of the branch is dense layer with the same size as radar branch. Thus, the two dense layers are then concatenated to a dense layer of size 200. The networks final output layer is the output of the classification result. The loss during the training is calculated by categorical_crossentropy function and the loss is minimized by using Adam optimizer.

IV. Experiments

Our model used radar RCS sequences and real-time images to train. The dataset includes 3,142 training data and 197 testing data. The result shows that the 2-branch model can identify the RCS signal as Abnormal and Normal labels. The training accuracy after 300 epochs is 95.54%. The confusion matrix, loss and accuracy plots are shown in Fig. 3.



(a) (b)

Fig. 3. Test dataset results expressed in confusion matrixes: (a) The loss and accuracy plot. (b) Testing dataset's confusion matrix.

V. Conclusion

In this paper, we find that the relationship between the radar RCS signal and distance to detect the radar fault. The experimental results show that the camera branch improves the detection rate. With the same car and same angle, the RCS signal is always at a normal range. With the radar feature, our model recognizes the input signal as normal and abnormal, and the accuracy improves to 95.54%.

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