Detection of Abnormal Radar Signal from RCS Sequence via CNN

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***Abstract*—Radar is widely used in autonomous driving technology, and maintaining its health is a necessary part of the safety of self-driving systems. The radar signal feature is reliable at recognizing pedestrians and vehicles, as well as detecting the surrounding environments. Sensor faults are unavoidable. When the radar sensor is faulty, the radar signal cannot receive feedback information accurately. We use the radar cross section (RCS) signal to detect faulty possibilities via the convolutional neural network.**

***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 stability. 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 faulty as a defect subcomponent, mechanical damage to sensor cover, layer on the sensor, mounting issue, security attack, unfavourable environmental condition, and crosstalk [1] in Fig. 1.

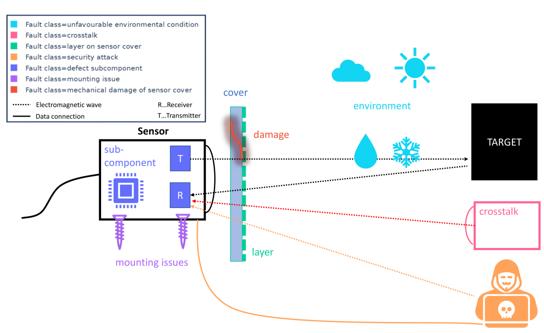


Fig. 1. Schematic illustration of sensor fault classes.

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].

People 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. 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 raise 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. What we need to do is make sure 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, use a web camera 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 advances and is further away from the vehicle, the radar RCS data will be collected from $5m$ to $50m$ distances.

This dataset collected RCS data on the three angles of the vehicle, front, side and back. 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. In total, 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 is contained with the obtained car's radar RCS and distance dataset leads $(time, dis, rcs)$ in the.csv file and its real-time images.

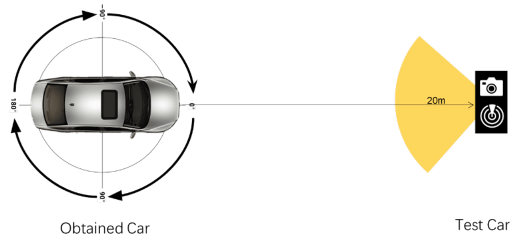


Fig. 2. Test progressing diagram.

With noise transaction preprocessing, we get clear signals for the training dataset via the CSV format and its real-time images. 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. 3 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 to 5 to 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.

III. Proposed Model

Our model is a two-branch network, with one branch identifying whether the RCS signal is normal or abnormal and the other being devoted to modelling the vehicle image, as shown in Fig. 3. 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 network 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 is used radar RCS sequences and real-time images to train. The dataset is include 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 96.50% and the testing accuracy is 88.14% which is shown in the Fig. 4.

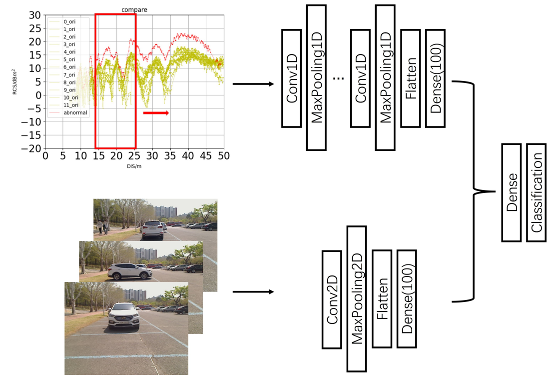
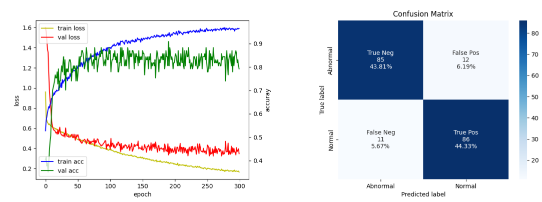


Fig. 3. Proposed model structure.



(a) (b)

Fig. 4. Test dataset results expressed in confusion matrixes: (a) The loss and accuracy plot. (b) Testing dataset's confusion matrix.

V. Conclusion

Using radar RCS signals to detect fault is challenging work because of the abnormal signal similarity with the normal signals. In this paper, we have developed a method to use the image information to help the RCS signal analysis. The result shows we can use the camera to assist detect the radar's fault happened. Future improvements of this work will include a more thorough design space exploration, to further the suitable and reliable abnormal signal generated to improve its performance in the real environment and the actual deployment of the proposed system on a real vehicle radar device.

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