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Stochastic Reliability Estimation of Deep Learning for Parking Vehicle Shape Estimation Using Millimeter Wave Radar

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Machine learning including deep learning can cause unexpectedly large errors for untrained data. This is an essential generalizability problem, and unavoidable in principle. It may cause fatal issues in safety-critical driver assistance systems. To address this concern, we have proposed various approaches to the problem of estimating the shape of parking vehicles using millimeter-wave radar so far. In this paper, we propose a method to estimate the reliability of each pixel from the stochastic error rate in estimated parking vehicle areas on a millimeter-wave radar grid map.

The entire dataset of radar maps and their ground truth of vehicle shapes is randomly divided into many small datasets. Then, a lot of sub-datasets are generated, one of which is the training data and the rest of them is the evaluation data. Fig. 1 shows the procedure to generate the error rate map dataset. The vehicle shape estimation network is trained on each training sub-dataset. The shape estimation is executed on the remaining data in the sub-dataset (evaluation data) by the shape estimation network using the trained network parameters. The error maps are calculated from the difference between the estimated map and the ground truth. The error rate map is generated by collecting the error map dataset frame by frame and calculating the number of errors relative to the total number of error maps for each pixel in the frame. The radar reflection map and the correct shape are used as inputs, and the reliability estimation network shown in Fig. 2 is trained using this error rate map as the ground truth of reliability. The reliability map is estimated by the network.

2099 radar maps measured for the actual parking scenes in urban areas as shown in Fig. 3 were used with the ground truth for the evaluation. The dataset was randomly divided into 5, 10 and 20 sub-datasets. The shapes were estimated for each one of them, and this was executed twice. The error rate map for each frame was calculated from the 70 estimated maps. The reliability estimation network was trained with the error rate maps and the ground truths. Samples of the reliability maps estimated for the shape maps estimated by the network trained with 5% of the dataset are shown in Fig. 4. (a) shows the reliability map in case of accurate shape estimation. The reliability for the vehicle shape was high, and ones for noises were low. These results seem reasonable. (b) shows the map for an inaccurate result. The reliability map for the left-hand vehicle is appropriate, on the other hand one for the right noise is incorrect. However, this reflection map looks like a partial car even when a human sees it. This is the limitation of a radar sensor itself.

This method can be applied to the high safety driver assistance system. We will challenge to create higher generalization method.

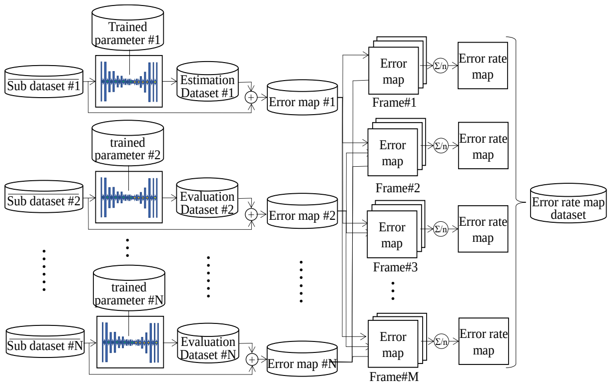


Fig. 1 Estimate car shape and generate error rate map dataset

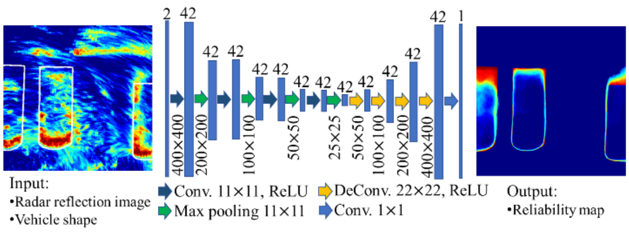
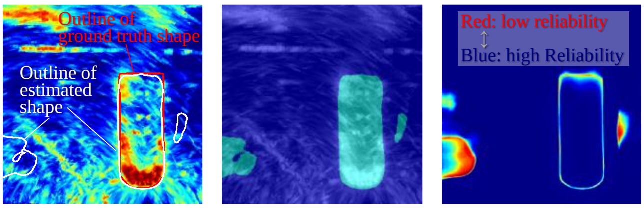
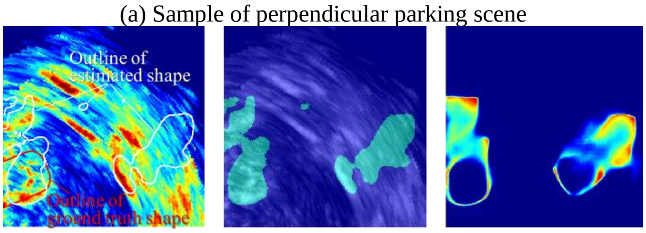


Fig. 2 Network structure to estimate reliability

Fig. 3 Image sample of measurement parking scenes



(a) Sample of perpendicular parking scene



(b) Sample of noisy and misleading radar map

Ground truth and estimated outline on radar map | Estimated shape on radar map | Estimated reliability map

Fig. 4 Sample of estimated reliability map with exceptional pattern