Description

Title of the Invention: System and Method for Anomaly Detection in High-Resolution Radar

The next generation radar operating in the mmWave band is able to achieve high resolution, long-range, and wide field of view (FOV) four-dimensional (4D) imaging, regardless of weather and time. The high-resolution point cloud imaging provides unprecedented information on the range, azimuth, elevation, and Doppler of the environment. Thus, it is emerging as one important sensor for advanced environment perception that paves the way for advanced driver-assistance system (ADAS), vehicular automation, industrial off/on road and many other applications of radars. Despite those advantages, radar is subject to the problem of ghost targets created by the multipath propagation of millimeter waves. Multipath, a well-known phenomenon in radar, is caused by multiple reflections of waves propagating between radar and targets. As for instance in the context of automotive radar, potential reflection surfaces are randomly distributed in the environment, due to, for example, roads, buildings, infrastructure, and even the vehicle targets themselves. Therefore, multipath may happen randomly in the radar images depending on the relative geometry between the radar and its surrounding environments. The presence of multipath may increase the computation load in the data processing for perception and the ensuing ghost target will confuse the decision in the ADAS functions and even trigger false reactions like phantom braking in the driving function planning. It is thus becoming one critical issue to be addressed in radar signal and data processing.

The existing approaches based on signal and data processing assume a certain physical model and require additional information and thresholding for multipath detection. However, due to the complex environment and relative radar and target geometry, those physical models may not be valid, and the conditions and thresholds to determine multipath may change from scenario to scenario. It is thus exceedingly difficult to generalize those methods to adapt to a dynamic environment. On the contrary, deep learning (DL) based methods have no explicit assumptions on any model and do not need ad-hoc thresholding. It is thus attractive in view of practical adaptivity. Meanwhile, this kind of method learns the detection rules from the data and is thus more robust to uncertainties caused by the mismatch between the parameterized model in the signal and data processing and the actual physical model underlying the wave propagation. In addition, it can scale with the amount of data and thus can keep improving its performance with the increment in data. Moreover, the computation capacity on edge and on the electronic control unit (ECU) of ego-car keeps growing which makes the implementation of DL model possible on commercial processors. Although there exist many works in this direction, there are challenges which are not fully considered and addressed in order to transform the techniques from research to a product. DL heavily relies on the availability of labeled training datasets which may be difficult to obtain in practice. The model should be designed in such a way that efficient implementation with reliable performance can be achieved. The existing work solves the two issues separately.

In this patent, we devise a comprehensive method to address multipath detection by solving the data labeling and model design in one system featuring the active learning framework where the algorithm can interactively query information sources to label new data points with the desired outputs. This invention consists of the following methods and systems.

Firstly, a method and system of model design and training is developed by making use of both labeled and unlabeled data. Instead of training the DL model with only labeled data, this invention trains the model with the assistance of unlabeled data which makes the model convergence faster and relieves the requirement for more labeled data.

Secondly, a method and system for processing the unlabeled data using the model trained is developed.

Thirdly, based on the output of the prediction, a method and system is developed for selecting the frames with high predicted confidence score as labeled data and selecting frames with low confidence score as labeled data for further correction.

This invention can be related to multipath detection in automotive radar but not limited just to automotive radar. More specifically, a system and method of multipath detection in the active learning framework are invented by addressing the data labeling and model design.

Brief descriptions of the drawing

Component-01 stands for a set of data without multipath labels. The amount of data under Unlabeled Data category may increase whenever new data are available from sensors.

Component-02 stands for the data with labels. Initially, those labeled data can come from manual labeling or other labeling methods such as semi-automatic labeling with both automatic labeling and human labeling/correction. Gradually, those amount of data will increase as the model is applied to inference on unlabeled data and generate new labels.

Component-03 stands for model design and training of the deep learning model. The input data to the model consists of both the labeled data and unlabeled data. The model will be trained using both labeled data and unlabeled data in such a way that general features relevant to the model prediction will be learned from both data and model prediction will be guided by the labeled data. The loss function will be constructed based on labeled data and unlabeled data alike. The model will be trained using both the labeled and unlabeled data by minimizing a loss function combining loss functions from both data and tuning the model parameters through back-propagation.

Component-04 stands for applying the trained model on some unlabeled data. The amount of unlabeled data to be processed by the model trained can be determined by the model performance and overall data to be labeled. If the model is of lower performance then a smaller amount of data can be processed. Gradually, as the model performance increases, more data can be processed in one iteration.

Component-05 stands for the prediction output from the model. The output usually has the form of probability distributed between 0 and 1.

Component-06 stands for the MP detection and pseudo-labels after applying certain detection scheme on the probability in component-05.
For example, a thresholding can be applied to the probability to determine if a point belongs to MP. Meanwhile, the probability can convey information of reliability for each MP detection and non-MP detection.

Component-07 stands for the process that select those labels with low reliability first followed by correction by other methods. After those labels being corrected, the data will be added to the labeled data for model training and design in the next iteration. Meanwhile, these data will be deleted from the unlabeled data.

Claims

Claim 1:

A method and system for detecting multipath in radar point cloud using a small number of labeled data and a large amount of unlabeled data are devised as depicted in Figure -1.

Claim 2:

A method and sub-system of model design and training from claim 1 using both labeled and unlabeled data in a semi-supervised training scheme i.e., combining a small amount of labeled data with a large amount of unlabeled data during training.

Claim 3:

A claim 1's method and sub-system of selecting and correcting the pseudo-labels from predicted labels to be included in the training data.