SHORT TERM SCIENTIFIC MISSION (STSM) – SCIENTIFIC REPORT

The STSM applicant submits this report for approval to the STSM coordinator

Action number: CA15127 - Resilient Communication Services Protecting End-user Applications from Disaster-based Failures (RECODIS)
STSM title: Validation of Noise Models for Signal Propagation under Adverse Weather Conditions
STSM start and end date: 11/06/2018 to 22/06/2018
Grantee name: Sinan Hasirlioglu, Technische Hochschule Ingolstadt, Germany

PURPOSE OF THE STSM/

Active and integral vehicle safety systems rely on data given by wireless communications, camera, lidar, and radar sensors. Using this information, safety systems can execute by-wire control actions in the pre-crash phase, i.e. before an accident actually occurs. These systems could thus be regarded as precursors on the way to autonomous driving. However, already small errors in sensor data measurements can lead to severe accidents, thus, testing the reliability of sensors and safety systems before market introduction is of high importance. Nowadays, in order to comply with functional safety standards such as ISO 26262, car manufacturers need to perform endurance trials for millions of kilometers. With increasing system complexity, the number of test kilometers required to safeguard all vehicle functions might increase up to billions of kilometers. Additionally, the increasing complexity of safety systems results in increased test effort and, as a consequence, longer development time.

To counteract, simulation will play a central role in future development and test of autonomous driving functions. It is common knowledge that especially adverse weather conditions such as rain degrade a sensor's performance and can result in incorrect perception. The research institute CARISSMA at Technische Hochschule Ingolstadt, Germany has experience in the investigation of effects of adverse weather conditions on automotive surround sensors. The test facility in Ingolstadt is equipped with an indoor rain simulator which enables measurements independent of local weather condition, season, or time of the day. Therefore, a defined scenario can be measured by automotive surround sensors under clear (ground truth) and rainy weather conditions. Further, the grantee developed sensor specific noise models for simulating the effects of rain based on the ground truth data in a post-processing step.

The purpose of this STSM is to validate the noise models based on real world data. Sensor specific data from a defined scenario are available with no rain, real rain and simulated rain. The real and simulated rain should affect the ground truth data in the same way.

Therefore, different statistical methods for calculating the similarity between two independent measurements will be investigated. Further, it will be verified if a generic validation method can be used for each sensor type. Otherwise, the validation needs to be designed for each specific sensor type.

The STSM fits the scope of WG2: Weather-based disruptions.

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DESCRIPTION OF WORK CARRIED OUT DURING THE STSMS

During the STSM, we analyzed statistical methods for calculating a measure for the similarity between two sensor measurements. Different sensors output data with different physical unit and quantity. We focused mainly on images, point clouds, and video signals (of radar sensors).

Generally it is assumed, that similarity can be calculated by metric distances such as Euclidean distance. It is known, that rain affects the sensor data highly random and can lead to extreme differences compared to the ground truth. Therefore, we focus on non-metric distances which are more robust to outliers.

Sensor data are often analyzed using histograms, especially in computer vision. Therefore, we investigated a histogram-based approach for validating all sensor data in the same way. The major advantage of a generic validation method is that the performance of noise modeling for different sensor types can be compared with each other. A generic validation method can be also used as a benchmark method.

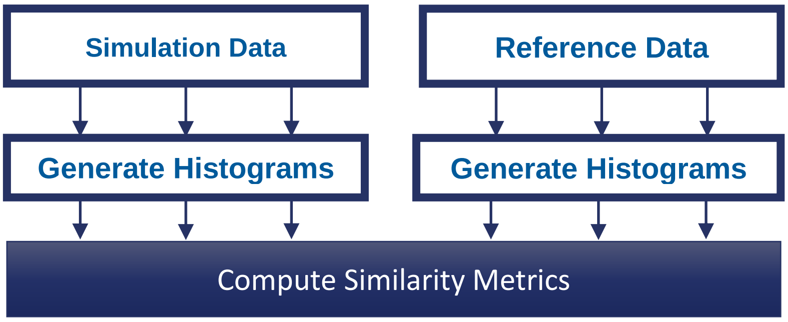

Figure 1: Histogram-based approach for validating the simulated output of each surround sensor in the same way.

We assume in a first step that the developed noise models are validated, when the similarity measure between real rain data and simulated data is higher than between real rain data and ground truth data. This concludes that the developed noise models enable testing towards adverse weather condition.

Similarity or dissimilarity measures of two histograms are divided into two categories. The bin-by-bin similarity measure compares the data of the corresponding histogram bin, where the cross-bin measure compares data using all bins. Due to the fact that the influence of rain is highly random, we decide to use the cross-bin method and focus on Match distance and the Kolmogorov-Smirnov distance. The Match distance is defined as the sum of all absolute differences between the corresponding cumulative histograms. The Kolmogorov-Smirnov distance is defined as the maximum absolute difference between the cumulative histograms. The smaller the value, the more similar the data.

Starting with the camera sensor, we generated the histograms of no rain, real rain, and simulated rain conditions. All histograms were converted to cumulative histograms, to enable the calculation of Match and Kolmogorov-Smirnov distance. Both metrics allow for this sensor type a clear statement about the similarity (see left image of Fig. 2). Next, we generated the cumulative histograms for the point clouds of a laser scanner (single layer) for all three conditions (see right image of Fig. 2). The Kolmogorov-Smirnov distance can also show the similarity between two point clouds but provide no detailed information. The Match distance lead to much better results due to the fact, that more data is used for the scalar similarity value. Finally, for radar sensors we generated the histogram of a single chirp. This leads to loss of range information and provide only information about the intensity distribution. The behavior that raindrops lead to increased reflections in the near field and decreased reflections in the far field is not being validated. Therefore, the similarity of radar video signals are calculated using rank correlation coefficients.

The histogram-based approach for validating noise models show good results for the optical sensors (camera and lidar), but does not meet the requirements for the radar sensors. Therefore, we reject the idea of a generic validation method and focus on sensor specific validation.

DESCRIPTION OF THE MAIN RESULTS OBTAINED

All calculation are performed using the software MATLAB.

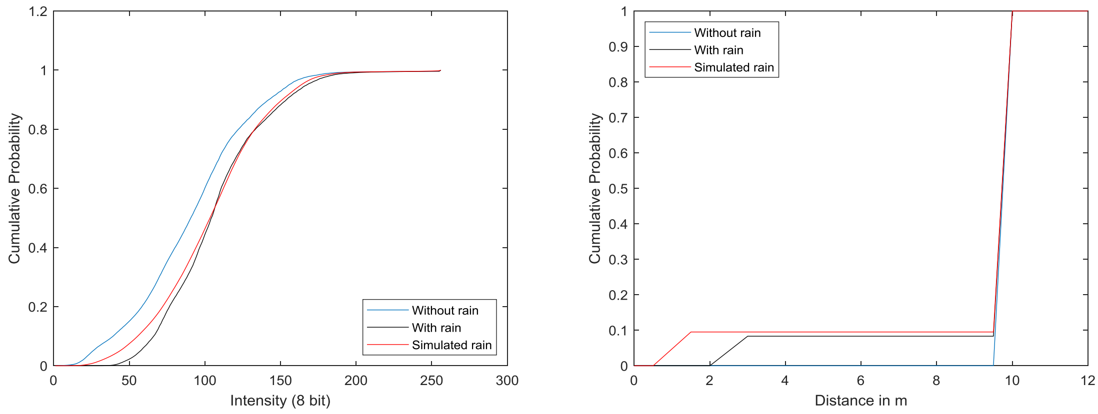

Figure 2: Cumulative histograms of camera images (left) and point clouds (right) including no, real, and simulated rain conditoins. The blue curve represents the condition without rain, the black curve the real rain condition, and the red curve the simulated rain condition. Static scenario: Target vehicle is placed at a distance of 10 m and is measured by camera, lidar, and radar sensors.

The left image of Fig. 2 shows the cumulative histograms of cameras images with no, real, and simulated rain. Each distribution origins from the same scenario and has identical number of information. It can be seen, that real rain lead to brighter images (right shift) and modified intensity distributions. The noise model aims to simulate the same effects. Visually, the red cure is more similar to the black curve, compared to the blue one. The Match distance between blue and black results in 15.91 and the Kolmogorov-Smirnov distance in 0.17. The Match distance between red and black results in 3.99 and the Kolmogorov-Smirnov distance in 0.06. It can be seen that the noise model simulated rain effects according to real rain. Both distance measures allow statements about the similarity of two images.

The right image of Fig. 2 shows the cumulative probabilities of point clouds depending on the distance of the scan points. Raindrops scatter the transmitted light back to the sensor which can lead to false positive scan points. This leads to near field scan points (see red and black curve). Note, that both cases (red and black) have 2 scan points in the near field. The difference result from different number of total scan points, which can result due to hardware inaccuracies. The Match distance between blue and black results in 1.21 and the Kolmogorov-Smirnov distance in 0.08. The Match distance between red and black results in 0.45 and the Kolmogorov-Smirnov distance in 0.1. Visually, the red curve is more similar to the black one, but results in a higher Kolmogorov-Smirnov distance value, which means less similarity. Therefore, instead of using Kolmogorov-Smirnov distance, we will use the Match distance for validating point clouds. The closer the near field reflection, the lower the Match distance, the higher the similarity.

For radar sensors, we focus on video signals. Radar sensors output intensity values for each range cell, whose size depends on the sensor configuration. It can be seen in the left image of Fig. 3, that real rain increases the reflections in the near field and decreases the reflection from the far field. Further, it decreases the object intensity. To stay consistent with the remaining similarity calculations of camera and radar, we generated a histogram of the video signal (see right image of Fig. 3). The main disadvantage is that we lose the range information and calculate inconclusive similarity measures. Therefore, we decided to use correlation values for comparing video signals, such as Spearman's rank correlation coefficient and Kendall's tau. The spearman correlation between the blue and black curve result in 0.48 and the Kendall's tau correlation value in 0.38. The spearman correlation between the red and black curve result in 0.54 and the Kendall's tau correlation value in 0.45. This show more representative the similarity between two graphs and further show the similarity of the simulation. Hence, we noticed that the correlation of the simulation is very low which means that we need to update our noise model in future work.

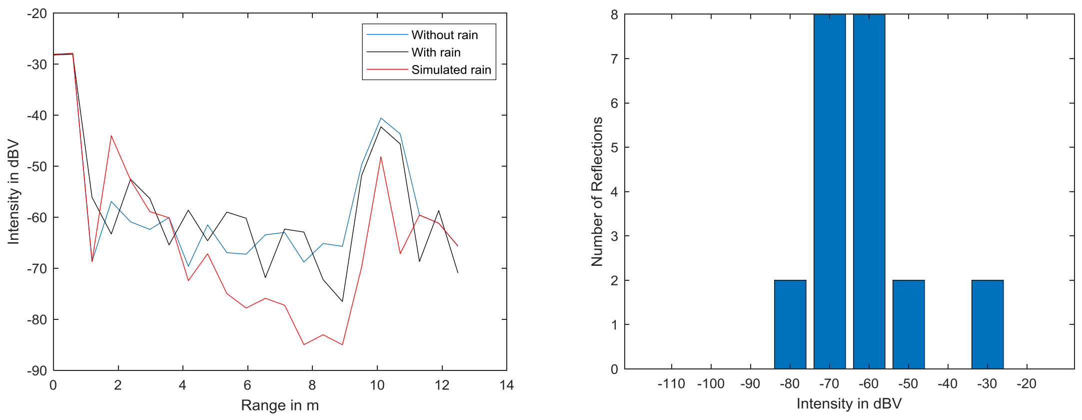

Figure 3: Left: Video signal of a radar sensor in no rain, real rain, and simulated rain conditions. The intensity in dBV is plotted depending on the range in m. Right: Histogram of the intensity values of the no rain condition.

In conclusion, it can be said that generic approaches have many advantages, but are not always constructive. We decide to validate the noise models using sensor specific validation methods.

In future work, the grantee adapts the noise model for increasing the level of realism of the modified surround sensor data. The validation should be repeated with the final noise models.

FUTURE COLLABORATIONS (if applicable)

The host supervisor Alexey Vinel from Halmstad University is invited from the grantee to the home university (Technische Hochschule Ingolstadt). A visit could probably be possible in Fall 2018 or Spring 2019.

Future collaboration are planned and will be discussed in detail.