Deep Interference Mitigation and Denoising of Real-World FMCW Radar Signals

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Abstract—Radar sensors are crucial for environment perception of driver assistance systems as well as autonomous cars. Key performance factors are a fine range resolution and the possibility to directly measure velocity. With a rising number of radar sensors and the so far unregulated automotive radar frequency band, mutual interference is inevitable and must be dealt with. Sensors must be capable of detecting, or even mitigating the harmful effects of interference, which include a decreased detection sensitivity. In this paper, we evaluate a Convolutional Neural Network (CNN)-based approach for interference mitigation on real-world radar measurements. We combine real measurements with simulated interference in order to create input-output data suitable for training the model. We analyze the performance to model complexity relation on simulated and measurement data, based on an extensive parameter search. Further, a finite sample size performance comparison shows the effectiveness of the model trained on either simulated or real data as well as for transfer learning. A comparative performance analysis with the state of the art emphasizes the potential of CNN-based models for interference mitigation and denoising of real-world measurements, also considering resource constraints of the hardware.

I. INTRODUCTION

Automotive radar sensors are key elements of current driver assistance systems and autonomous driving applications. In the automotive context, frequency modulated continuous wave (FMCW)/chirp sequence (CS) radars are prevalent. They transmit sequences of linear chirp signals in a shared and non-regulated spectrum. Ever larger radio frequency (RF) transmit bandwidths are required to fulfill the demand on fine range resolution. Because of these larger bandwidths and because of a rising number of deployed radar sensors, mutual interference is becoming increasingly likely.

Non-coherent interference, in which radar sensors with non-identical transmit signal parameters interfere, is the most common form of mutual interference \cite{1}. This leads to a reduced object detection sensitivity \cite{2}. Therefore, interference mitigation is a crucial part of current and future radar sensors used in a safety context.

Several conventional signal processing algorithms have been proposed in order to mitigate mutual interference. The most basic method is to zero out the interference-affected signal samples. More advanced methods use nonlinear filtering in slow-time \cite{3}, iterative reconstruction using Fourier transforms and thresholding \cite{4}, estimation and subtraction of the interference component \cite{5}, or beamforming \cite{6}. Some machine learning techniques were discussed in the context of interference detection and classification in \cite{7}.

Convolutional Neural Networks (CNNs) have been successfully used for image denoising, e.g. in \cite{8}. CNN-based interference mitigation and denoising methods presented in \cite{9} can be applied to range-Doppler (RD) maps. A two-channel representation of the complex spectrogram data (i.e. real and imaginary data) is used as network input. Experimental results show a strong denoising and interference mitigation capability in comparison to state-of-the-art signal processing algorithms, though evaluated only on simulated data. The applicability of these models for robust interference mitigation on real-world data has not been investigated so far.

Denoising Autoencoders (DAEs) \cite{10} and Generative Adversarial Networks (GANs) \cite{11}, \cite{12} have been used for RF signal denoising, applied either in time domain or in frequency domain. These models achieve promising denoising performance, however, they typically require more learnable parameters and more complex model structures and thus are less suitable for deployment on resource-restricted hardware. Residual learning \cite{8}, \cite{13}, \cite{14} has successfully been used for denoising of unstructured noise.

In this paper, we analyze the suitability of CNN-based models from \cite{9} to perform interference mitigation and denoising on real-world radar measurements. Therefore an extensive measurement campaign in a typical inner-city road traffic scenario has been carried out. The interference is simulated for both, simulated object scenarios and real-world measurements.

Due to the absence of labeled object positions in the target RD maps, we use the cell averaging constant false alarm rate (CA-CFAR) algorithm \cite{15} to identify the most likely object positions. These positions are the basis for our performance comparison using the signal-to-interference-plus-noise ratio (SINR) \cite{16}.

Main contributions of this paper are:

- We consider real-world radar measurements combined with simulated interference for CNN-based interference mitigation and denoising of RD maps.
- We compare performance and model complexity on simulated and measurement data to show that already small models yield good results.
- We analyze the effect of finite sample sizes on model performance and robustness.
- We present numerical results using application-related performance metrics in a comparison with the state of the art, i.e. Zeroing, IMAT and Ramp filtering.
with random distances and velocities to model the object reflections. Real measurements already contain object reflections mixed with receiver noise. In both cases, the interference is simulated and added to the time domain object reflections according to Equation (1). Noncoherent mutual interference essentially generates time-limited broadband disturbances, see [11], [19] for details.

State-of-the-art (“classical”) interference mitigation methods are mostly signal processing algorithms that are applied either on the time domain signal $s_{\text{IF}}[n, m]$ or on the frequency domain signal $S_R[n, m]$ after the first DFT. The CNN-based method used in this paper, also denoted Range-Doppler Denoising (RDD), is applied on the RD map after the second DFT.

### III. CNN model architecture

The interference mitigation and denoising CNN architecture is based on the models from [19]. Range Doppler Denoising (RDD, as labeled in Figure 1) is used for evaluation and comparison, because of its superior performance on past experiments with simulated data.

Figure 2 illustrates the CNN-based architecture, which consists entirely of convolutional composite layers. The first layer performs convolution operations and ReLu [20] activation functions; subsequent layers additionally include Batch Normalization (BN) [21]. An exception is the last layer, which uses a linear activation function and two kernels in order to map to the real and imaginary data. The amount of kernels in a layer is chosen to be a power-of-two and decreasing for subsequent layers, e.g. $[2^6, 2^5, 2^4, 2^2]$, as inspired by [14].

RDD is applied to radar snapshots after the second DFT (RD maps), hence the input samples are complex valued patches of size $N \times M$. Square kernels are used in combination with zero-padding, such that the inputs and outputs for each layer have the same spatial dimension. We use two input channels in order to represent the real- and imaginary parts of the complex valued input. For training the network we use the mean squared error (MSE) loss function and the Adam [22] algorithm.

### IV. Experimental setup

#### A. Data sets

In our experiments we evaluate two data sets. The first one is purely simulated including object reflections, noise and interference. The second data set consists of real-world measurements, that are combined with simulated interferences. This way we have access to training inputs and their corresponding targets with a limited measurement expenditure. Nevertheless, realistic scenarios are the basis of training and evaluation, and thus give an insight of interference mitigation performance on real-world data. Both data sets are split into three partitions for training (2500 snapshots), validation (250 snapshots) and testing (250 snapshots) the models. Data from a single measurement, consisting of 32 snapshots and sixteen antennas, are exclusively contained either in the training, validation, or test set.
TABLE I: Ranges of interference and noise parameters.

| Parameter | Value       |
|-----------|-------------|
| f_{0,I}   | 78.9GHz     |
| f_{1}     | 0.15GHz     |
| f_{T}     | 12μs        |
| SNR       | -15.5dB     |
| SNIR      | -5.5dB      |

TABLE II: Ego radar and signal processing parameters for simulation and measurements.

| Parameter | Value       |
|-----------|-------------|
| f_{0,I}   | 79GHz       |
| f_{1}     | 0.27GHz     |
| f_{T}     | 12.8μs      |
| f_{RFV}   | 10MHz       |
| N         | 512         |
| M         | 128         |
| A         | 16          |
| w         | Hann        |

1) Simulation: The basic receive IF signal is generated according to (1) and processed as described in Section II. The signals are generated based on several parameters, that are sampled from uniform distributions $U([\text{min}, \text{max}])$ in the respective domains. Among them are the number of objects $U(1, 20)$ and for each object the relative distance $U(0m, 100m)$ and velocity $U(-20m/s, 20m/s)$.

The interferer parameters are uniformly sampled within the ranges listed in Table I while the ego radar parameters (see Table II) are constant for all simulations. The signal-to-noise ratio (SNR) and the signal-plus-noise-to-interference ratio (SNIR) are used to scale the noise and interference powers relative to the object-signal power and object-signal-plus-noise power respectively, when generating the interfered and noisy time domain signal $s_{n,m}$.

Figure 3 shows a RD map processed from a simulated signal with five objects, where Figure 3(a) shows an interfered signal and Figure 3(b) shows the corresponding clean data with AWGN.

2) Real-world measurements: The measurements were recorded in typical inner-city traffic scenarios. We used a cargo bicycle with a radar apparatus mounted on the front and additional measurement equipment in the cargo container. The device was configured according to the parameters in Table II. One measurement denotes 32 consecutive snapshots recorded with sixteen antennas, where each measurement snapshot is associated with a wide-angle camera picture for reference. An input sample for the CNN, i.e. a RD map, is processed from one measurement snapshot of a single antenna.

The measurement signal consists of object reflections (static and moving) as well as receiver noise. The interference is simulated as described in Section IV-A1. The SNIR is used for scaling the interference relative to the object signal plus receiver noise power. Figure 4 shows a RD map processed from a real-world measurement, where Figure 4(a) shows an interfered signal, Figure 4(b) shows the corresponding clean signal and Figures 4(c) shows the respective camera snapshot for reference.

3) Experimental analysis of simulation and measurements: The simulated signal is modeled according to reflections from point objects, which results in single, clear and well-shaped object peaks in the RD map. All distances, velocities and angles are randomly sampled, i.e. there is no observable bias towards object peak positions in the RD map.

In the real-world measurements on the other hand, we observe more complex objects, which consist of object peak clusters that are often distributed along the distance as well as the velocity axis of the RD map. Furthermore, a strong bias of object velocities towards the negative velocity of the measurement vehicle is present. This bias results from static objects; they are contained in velocity bins close to the negative ego velocity. Also, there exist strong reflections within the first few meters at a relative velocity of zero, i.e. the reflections of the radar and the measurement vehicle themselves. Another bias, though less severe, can be observed regarding the physical positions of moving objects, caused by the relative position of bicycle lanes to car lanes in the measurement environment.

B. Performance measures

1) Quantitative measures: The signal-to-interference-plus-noise ratio (SINR) is used as performance measure. It is defined as the ratio of signal power at the object peaks to the noise floor [12]. The SINR directly relates to the object detection sensitivity [16], i.e. it significantly influences the chance that an object is detected on the RD map.

The CA-CFAR detector [13] is used to find the RD map positions of the most prominent object peaks in both the simulated and the measurement data. We apply the detection
algorithm with a window of $6 \times 8$ and two guard cells in each dimension. For peaks close to borders, we only consider cells lying within the RD map as reference window cells.

2) **Qualitative measures:** During visual inspection of the RD map, we consider criteria such as object peak and noise floor magnitude, object peak location, resolution and distortion as well as artifact appearances.

C. **Mitigation methods selected for comparison**

Zeroing \cite{23}, Iterative method with adaptive thresholding (IMAT) \cite{24} and Ramp filtering \cite{3} are chosen as representative state-of-the-art signal processing algorithms for comparison. See \cite{9} for an overview of these methods.

Note that zeroing and IMAT require the detection of interfered IF signal samples. In this paper the detection step is assumed to be optimal. In practice however this is not the case, which may have a strong impact on the performance of these algorithms \cite{16}.

V. **Experimental results**

First, an extensive parameter search is performed to find suitable CNN-architectures for the simulation and measurement data sets each. The best model architecture is used for all simulations, because of its clear superiority on past experiments. For these evaluations we use the same test set, namely with real measurements, and vary the training set consisting either of the simulated data, real measurements, or both in the context of transfer learning. Finally, we provide a performance comparison with classical interference mitigation methods.

A. **Parameter search for a suitable CNN-architecture**

All models are based on the architecture described in Section III. In order to find suitable hyper parameters, we run simulations using a different number of layers ($2, 3, \ldots, 10$) and maximal number of kernels ($2^n, n = 3, 4, \ldots, 8$). A kernel size of $3 \times 3$ is used for all simulations, because of its clear superiority on past experiments.

Figure 5 shows the SINR based performance comparison of all evaluated architectures. The performance-to-model-complexity relation can be observed in Figure 5(a). Results for simulated (light blue) and real measurement (dark blue) data are shown with regard to the number of CNN-parameters. The clean and interfered SINRs, denoted SINR$^\text{Clean,Real}$ and SINR$^\text{Interfered}$, are marked with a horizontal line in the corresponding color. The best performing models (A, B) and the smallest models with acceptable performance (C, D) are labeled and respective details are listed in Table III.

The respective best model for each data set reaches outstanding interference mitigation and denoising performance with SINR$^\text{Sim}$ = 29.03 dB and SINR$^\text{Real}$ = 32.71 dB. Note, that this metric is significantly higher than the SINR of the 'clean' data without interference, i.e. SINR$^\text{Clean}$ = 27.95 dB and SINR$^\text{Real}$ = 27.72 dB. Thus, the CNN-based models are well suited for the interference mitigation task and have an additional denoising effect. Also, the required model sizes are very small in the context of deep learning. Already models with less than $10^3$ parameters produce excellent results for both data sets. Models for simulated data require even less parameters than models for measurement data in order to reach the 'clean' SINR. The small variance and high values over different network architectures when trained on simulated data indicates more robustness regarding the choice of hyper parameters. Note, that for measurement data the maximal achieved SINR improvement is higher than for simulated data.

Figures 5(b) and 5(c) analyze the performance on measurement data according to the amount of CNN layers and convolutional kernels respectively. A high mean and low variance without negative outliers per hyper parameter indicate good performing and robust CNN model architectures. Thus, models with 3 to 9 layers and 16 to 512 kernels per layer indicates a robust training process and denoising performance. We choose an architecture with 4 layers and $[512, 32, 16, 2]$ kernels in these layers for further evaluations.

B. **Finite sample size performance comparison on real-world data**

We investigate the interference mitigation and denoising capabilities on real measurements dependent on the amount of training samples. Therefore the same test set, namely with measurement data, is used for all evaluations. For training we consider three different data sets consisting of: simulated data (Sim), measurement data (Real), and both, simulated data to pre-train the model and measurement data for fine-tuning, in the context of transfer learning (Transfer). In the case of simulated training data, we run simulations using also simulated data for

| Marker | Note | Data | Layers | Kernels | Parameters | SINR |
|-------|------|------|--------|---------|------------|------|
| A     | Best | Sim  | 2      | 64      | 2370       | 29.03 dB |
| B     | Best | Real | 7      | 512     | 1582834    | 32.71 dB |
| C     | Small| Sim  | 2      | 16      | 594        | 28.02 dB |
| D     | Small| Real | 3      | 8       | 898        | 28.73 dB |
validation (Sim), and using measurement data for validation (Sim+VReal). For each data set we train the model using 50, 100, ..., 600 samples. In the case of transfer learning, we pre-train the model with 500 simulated samples and fine-tune with the respective amount of measurements.

Figure 6 shows the relation of SINR performance to the number of samples in the training set. The top and bottom figures show the mean and variance of the SINR, based on twenty simulations per configuration using a randomly selected training subset.

According to our evaluations, also the training with simulated data results in a very high interference mitigation and denoising performance. This indicates, that our model indeed learns to remove the interference and noise instead of learning the object scenarios. Naturally, the outstanding performance is possible, because we use simulated interference also for testing. Nonetheless, the evaluation shows, that interference mitigation can be generalized to unseen object scenarios, such as real-world measurements, as long as realistic interference is used during training.

Training on simulated data seems to be very stable according to the small variance over all training set sizes. This may result from the simpler nature of simulated data, which is beneficial for the learning process. Whether simulated (Sim) or real (Sim+VReal) data is used for validation does not seem to have a strong influence on the performance.

For training with measurement data and transfer learning, the SINR is reduced for fewer training samples; it increases with a rising number of samples until it reaches $\text{SINR}_{\text{clean}}$ with around 400 samples and surpasses the performance of models trained on simulated data with 450 (Real) or 500 (Transfer) samples. During this rise of mean SINR, the variance increases as the model’s training progress highly depends on the significance of the randomly sampled training subset. With more than 300 samples, the variance drops again and stabilizes at a low level with more than 500 samples. Advantages of transfer learning over training with measurement data can only be observed for a very small amount of training samples (50 samples) and thus is not considered beneficial for our experiments.

Fig. 6: Relation of SINR to the number of samples in the training set.

C. Performance comparison with classical interference mitigation methods

Three classical interference mitigation methods, as described in Section IV-C, were implemented and evaluated using SINR. The results are statistically compared to the CNN-based model, that was trained and validated on 2500 and 250 measurement snapshots, respectively. For the evaluation we used a Monte-Carlo-Simulation with 250 measurement snapshots. Figure 7 shows the empirical cumulative density function (CDF) of their evaluated SINR values. The 'clean' measurement and interfered signals are included as reference. One of the measurement snapshot RD maps with interference, without interference and with mitigation using the CNN-based model is displayed in Figure 8.

The three classical methods, i.e. zeroing, IMAT and Ramp filtering, all improve the SINR slightly in measurement snapshots with strong interference. For moderate to weak interference on the other hand, they are not capable of removing interference effects and even decrease the SINR of the interfered signal, i.e. perform worse than without mitigation. The CNN-based model outperforms the classical methods for all tested interference
and NVIDIA by providing GPUs.

The most important task in the future is to collect real interference measurements and to evaluate the generalization capabilities of the CNN-based models on these data.

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