V2V-Aided Adaptive FMCW Radar Interference Mitigation

Deniz Kumlu
Radar Research Department
Teraki GmbH
Berlin, Germany
deniz.kumlu@teraki.com

Muhammad Arsalan
Radar Research Department
Teraki GmbH
Berlin, Germany
muhammad.arsalan@teraki.com

Fabian Harrer
Radar Research Department
Teraki GmbH
Berlin, Germany
fabian.harrer@teraki.com

Ernesto Horne
Radar Research Department
Teraki GmbH
Berlin, Germany
ernesto.horne@teraki.com

***Abstract*—This paper addresses the challenge of interference mitigation in frequency modulated continuous wave (FMCW) radar systems by leveraging signal processing techniques and vehicle-to-vehicle (V2V) communication. The proposed method utilizes the short-time Fourier transform (STFT) to convert 1D radar signals into a 2D domain, enabling the application of robust principal component analysis (RPCA) for interference mitigation. A novel approach is proposed to dynamically adapt the RPCA λ parameter by leveraging aggressor radar parameters shared via V2V communication. Simulation results demonstrate that increasing the number of interfering radars and their amplitudes necessitates higher λ values for effective interference mitigation. Furthermore, the findings reveal that the incorporation of interfering radar parameters enhances signal reconstruction quality, particularly for weak target signals that are otherwise masked by interference. These preliminary results highlight the potential of adaptive λ selection, informed by V2V communication, to improve radar performance in real-time and support advanced autonomous vehicle systems.**

***Index Terms*—radar, interference, RPCA, V2V communication**

I. Introduction

Radar technologies have become increasingly popular in vehicles due to their sensing and detection capabilities combined with low cost. With the growing demand for autonomous vehicles, the use of radar sensors has increased, despite the limited electromagnetic spectrum allocated to the industry between 76 and 81 GHz.

Today, many cars are equipped with multiple radar sensors. When multiple vehicle sensors are active, it is unavoidable to observe interference between these radars. This interference has a increasingly adverse effect on radar detections, especially critical in dense traffic situations [1].

The principle of radar operation is rather simple. Automotive radars function as both transmitters and receivers of electromagnetic (EM) waves in the radar spectrum. The radar emits a wave that propagates through the air until it encounters an object, where it is partially reflected back to the sensor (and in many other directions). The target is identified through the physical characteristics of the reflected EM wave.

The process of identifying the reflected EM wave can vary, but what is common to almost all automotive radars is the use of frequency-modulated waveforms. The frequency of the waveform increases linearly with time to form what is known as a chirp. This particular waveform shape allows for comparison of the emitted wave with the reflected waves using heterodyne detection.

The radial distance between the sensor and the object is given by the frequency of the resulting plane wave. This concept can be extended to multiple targets by considering the resulting wave as a sum of multiple plane waves, each with a given frequency associated with the distance of the reflecting object. Through standard methods, such as the fast Fourier transform (FFT), the frequency spectrum can be easily obtained to identify the radial distance of the targets. This is apparent in the temporal domain. However, the power of the wave, and thus its frequency, is affected by several factors such as propagation, reflection, scattering, etc. [1].

In the case of multiple radar sources, parasitic signals (interference) from aggressor radars can be interpreted as reflections from the radar's own source. This results in interference or ghost targets due to misinterpretation of the frequency of the interfered wave. Additionally, because the intensity of the interfered wave is not decreased by any reflection, it can completely obscure the signal that contains real reflections [2].

This study explores the relationship between the robust principal component analysis (RPCA)'s λ penalization parameter [3], specification of frequency modulated continuous wave (FMCW) radars and interference characteristics. Using vehicle-to-vehicle (V2V) communication [4], key radar parameters, such as the number of interferences, frequency slopes, and signal amplitudes, are shared between vehicles to guide the selection of the optimal λ. The proposed interference mitigation strategy involves transforming 1D raw radar signals into 2D representations via a a short-time Fourier transform (STFT), applying RPCA to remove interference, and reconstructing the target signal using inverse STFT (ISTFT). The results show that λ is highly dependent on interference characteristics, with lower values suitable for single interferers and higher values required for multiple interferers. This dependency can be modeled through polynomial fitting, enabling real-time λ adaptation based on shared radar parameters, thus improving the performance and adaptability of RPCA.

This work is supoorted and funded by Teraki GmbH.

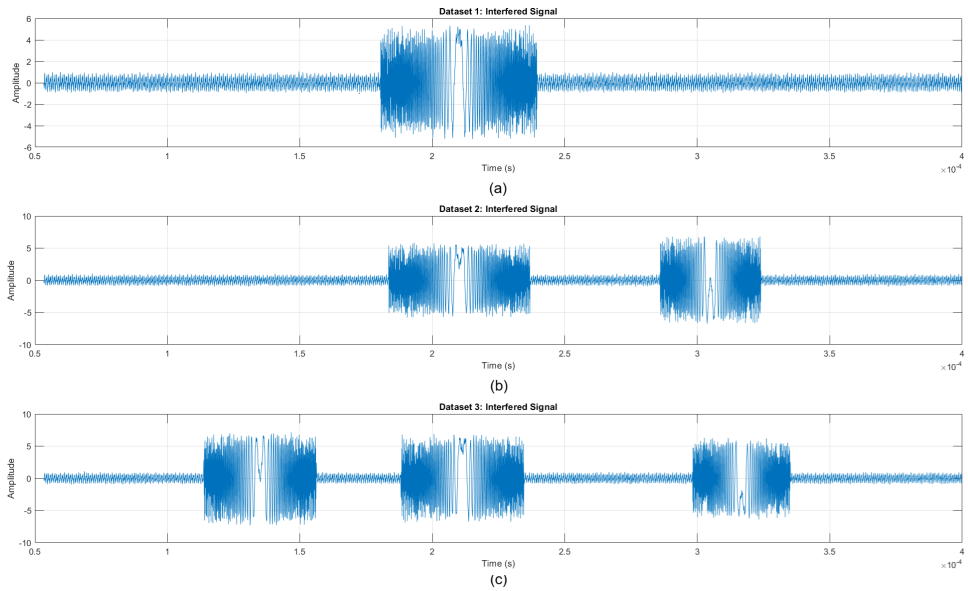

Fig. 1. Interfered signals from scenarios (a)–(c) with varying numbers of interferers, frequency slopes, and amplitudes.

II. Related Works

Interference mitigation in FMCW radar systems has been extensively explored using both signal processing methods and advanced machine learning techniques. Brooker [2] highlighted the significance of addressing mutual interference in FMCW radar systems, emphasizing its impact on reliable radar operations in dense environments. Fischer et al. [5] demonstrated that interference significantly affects the detection of weak targets in urban settings, raising the noise floor and complicating target identification. These foundational studies have paved the way for developing advanced interference mitigation methods.

Recent approaches have integrated sparse reconstruction and adaptive filtering techniques to mitigate interference. Correas-Serrano and Gonzalez-Huici [6] introduced orthogonal matching pursuit (OMP) for sparse reconstruction of chirplets, enabling effective separation of interference from target signals with minimal distortion. Similarly, Barjenbruch et al. [7] proposed an interference detection and cancellation method based on time-frequency analysis, leveraging the maximally stable extremal regions (MSER) algorithm to identify and suppress interference. This approach significantly enhanced the detection of weak targets obscured by interference.

Machine learning-based techniques have also been utilized to improve radar signal processing. Liu et al. [8] introduced the interference recognition network (IRNet), which leverages autocorrelation features to identify and mitigate interference in automotive radar systems. This method showcases the potential of neural networks in handling complex interference patterns in challenging scenarios. Additionally, Wang et al. [9] applied sparse and low-rank Hankel matrix decomposition to effectively mitigate interference in radar signals, achieving robust results in high-interference environments. These contributions highlight the importance of combining classical and data-driven methods to achieve robust radar interference mitigation.

TABLE I
Scenario's KPIs: Number of Interferers, Frequency Slopes, and Signal Amplitudes

Scenario	# of Interferers	Frequency Slopes (Hz/s)	Signal Amplitudes
1	1	$[2.8 \times 10^{11}]$	$[4.5]$
2	2	$[3.0 \times 10^{11}, -1.8 \times 10^{11}]$	$[5.0, 6.0]$
3	3	$[3.3 \times 10^{11}, -1.9 \times 10^{11}, -1.5 \times 10^{11}]$	$[6.0, 5.5, 6.5]$

III. Dataset Preparation

The simulated dataset consists of three distinct scenarios designed to evaluate interference mitigation techniques in radar systems. Each scenario varies in the number of interferers, frequency slopes, and signal amplitudes, allowing for comprehensive analysis of interference characteristics. The dataset specifications are detailed in Table I outlines the parameters for each scenario, which were selected to introduce variability, while deliberately increasing the complexity of the interference. The corresponding interfered signals for these scenarios are visualized in Figure 1, illustrating the impact of these interference configurations. The primary purpose of this dataset is to serve as a benchmark for exploring and validating the dependency of the RPCA λ parameter on interference features, facilitating the development of adaptive interference mitigation strategies in vehicular radar systems.

IV. Proposed Method

Interference in radar signals is generally much stronger than the desired reflected signal, as described by the Friis space propagation equation. The nature and impact of interference are influenced by the total interference power and the level of synchronization between the victim and the interfering radar (aggressor radar). Consequently, the reflection from the target can be significantly dominated by interference.

The received radar signal is represented as a 1D vector, denoted by x, with dimensions $N \times 1$. This signal can be either real or complex and contains coefficients with varying amplitudes.

To apply low-rank and sparse decomposition (LRSD) based matrix decomposition techniques, the received 1D radar signal must be converted into a 2D matrix form. It is crucial to represent the target or interference as a sparse component in the 2D matrix. In FMCW, the beat signal is typically sparse in the frequency domain. However, interferences at the Analog-to-Digital Converter (ADC) output generally exhibit sparsity in the time, frequency, or time-frequency domains under various scenarios.

The transformation of the received 1D radar signal x into a 2D matrix form, represented by X, can be achieved via methods such as the STFT.

A. Short-Time Fourier Transform (STFT)

The STFT is a powerful tool for analyzing non-stationary signals by providing a time-frequency representation. The STFT of a 1D signal $x(t)$ is defined as:

$$X(t,f) = \int_{-\infty}^{\infty} x(\tau) w(\tau - t) e^{-j2\pi f \tau} d\tau \tag{1}$$

where $w(\tau - t)$ is a window function that slides along the time axis t. The choice of the window function and its length affects the resolution of the STFT. The STFT converts the 1D signal into a 2D time-frequency representation, making it suitable for LRSD methods.

To apply the STFT to the 1D radar signal x, the signal is divided into overlapping segments. Each segment is windowed, and the Fourier Transform is applied to each windowed segment. This results in a 2D matrix where one dimension represents time and the other represents frequency. The STFT tranform of the scenario 3 is shown in Figure 2(a). This matrix can then be processed using LRSD techniques.

B. Low-Rank and Sparse Decomposition (LRSD)

In LRSD methods, the input matrix is modeled as the superposition of multiple signals corresponding to the low-rank and sparse components, which can be formulated as [3]:

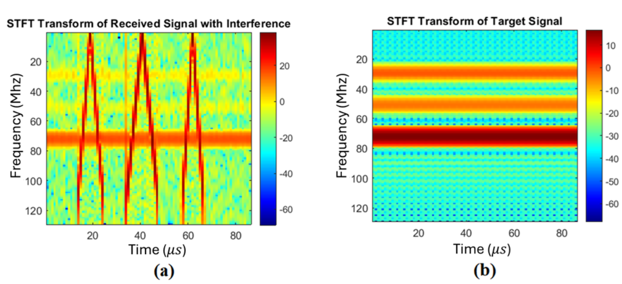

Fig. 2. 2D representation of the signal (a) STFT transform of the received signal with interference, (b) RPCA reconstruction of target signal.

$$X = L + S \tag{2}$$

Here, $L \in \mathbb{R}^{M \times N}$ represents the target component, and $S \in \mathbb{R}^{M \times N}$ represents the interference component. The input matrix is obtained by applying the STFT to a 1D ADC signal, resulting in a 2D time-frequency representation, where M denotes the number of time frames corresponding to the number of overlapping windows used in the STFT, and N denotes the number of frequency bins determined by the FFT size, reflecting the spectral resolution. Both L and S can be recovered from the input data matrix $X \in \mathbb{R}^{M \times N}$ through rank minimization techniques. Given the non-convex nature of this problem, a convex solution can be approximated via nuclear norm minimization. RPCA [3] addresses this minimization problem as follows:

$$\min_{L,S} \|L\|_* + \lambda \|S\|_1 \quad \text{s.t.} \quad X = L + S \tag{3}$$

In this equation, $\|\cdot\|_*$ denotes the nuclear norm, $\|\cdot\|_1$ stands for the L1-norm, and λ is a penalization parameter. RPCA is computationally intensive due to the iterative singular value decomposition (SVD) operations involved. For efficient rank minimization, one may employ non-convex matrix factorization techniques for faster low-rank recovery.

Figure 2(b) illustrates the reconstructed target component of the signal, where the interference-mitigated 1D signal is recovered through the application of the ISTFT transformation.

V. Experimental Results

To evaluate the effectiveness of the STFT and RPCA-based interference mitigation strategy, we conducted a series of experiments on the simulated scenarios. Figure 3 demonstrates the FFT results of the raw signal with interference for the most complex scenario, the original target signal, and the reconstructed signal obtained after applying RPCA (scenario III). The top subplot shows the FFT of the raw signal with interference, where a weak target is masked by the elevated noise floor caused by strong interference. The middle subplot represents the FFT of the original target signal (without interference), revealing clear peaks corresponding to the actual targets.

After applying RPCA with the optimal λ value, the bottom subplot highlights the FFT of the reconstructed signal. It can be observed that the weak target that was previously obscured by interference is now clearly visible. The results indicate that RPCA effectively mitigate interference, reconstructing the weak radar target and closely approximating the original target signal shape. This emphasizes the effectiveness of RPCA in reconstructing target signals, even under challenging interference conditions.

Figure 4 further evaluates the relationship between the λ parameter and reconstruction quality by showing the mean squared error (MSE) for various λ values across different scenarios. Each subplot corresponds to a different interference scenario described in Figure 1, where the number of interferers, frequency slopes, and signal amplitudes vary. In each case,

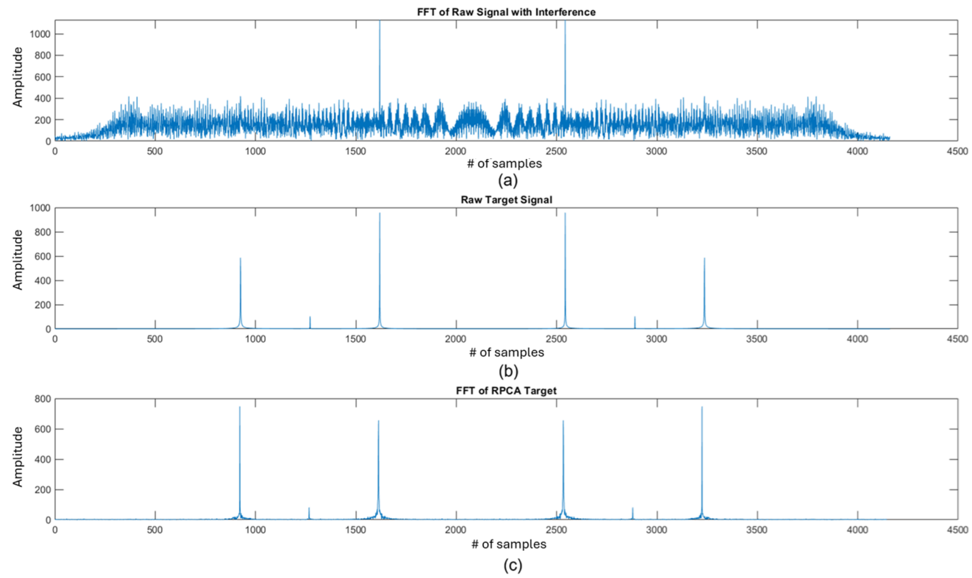

Fig. 3. FFT results of the Scenario III (a) signal with interference, (b) original target signal (c) reconstructed target signal via RPCA.

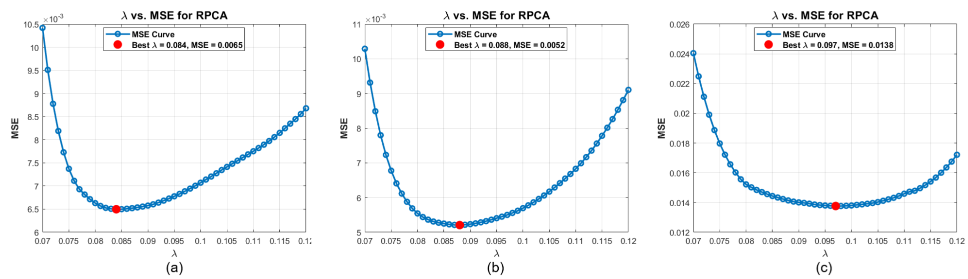

Fig. 4. Best λ vs. MSE for RPCA based target reconstruction: (a) scenario I, (b) scenario II, and (c) scenario III.

a grid search for the optimal λ was performed to minimize the MSE between the reconstructed signal and the original target signal and optimal points are shown in the Figure 4.

The obtained results demonstrate that the optimal λ value is directly effected by the interference characteristics and agressor radar spesifications. Scenarios with fewer interferers and lower amplitudes correspond to smaller λ values, while scenarios with more challenging interference require larger λ values for effective mitigation. This dependency highlights the importance of adaptively tuning λ based on interference characteristics shared via V2V communication.

VI. Conclusion

This study demonstrated that the selection of the optimal penalization parameter in LRSD methods, specifically RPCA, is influenced by the characteristics of interfering radars. By utilizing V2V communication to share parameters such as the number of interferers and their spesifications, we showed that the robustness of interference mitigation strategies can be enhanced. The proposed approach effectively improves weak target reconstruction, showcasing its potential for advancing radar system performance in challenging environments.

References

[1] C. Waldschmidt, J. Hasch, and W. Menzel, "Automotive radar—From first efforts to future systems," *IEEE Journal of Microwaves*, vol. 1, no. 1, pp. 135-148, 2021.

[2] G. M. Brooker, "Mutual Interference of Millimeter-Wave Radar Systems," *IEEE Transactions on Electromagnetic Compatibility*, vol. 49, pp. 170-181, 2007.

[3] E. J. Candès, X. Li, Y. Ma, and J. Wright, "Robust principal component analysis?," *Journal of the ACM (JACM*, vol. 58, no. 3, pp. 1-37, 2011.

[4] G. Andújar, I. Puente, I. de Diego, and E. Gil, "Car2Car Communication Using a Modulated Backscatter and FMCW Radar," *Sensors*, vol. 21, no. 11, p. 3656, 2021.

[5] C. Fischer, C. Waldschmidt, and R. Weigel, "Impact of interference in automotive radar sensors," *2013 European Radar Conference (EuRAD)*, pp. 133–136, 2013.

[6] A. Correas-Serrano and M. A. Gonzalez-Huici, "Sparse reconstruction of chirplets for automotive FMCW radar interference mitigation," *IEEE MTT-S International Conference on Microwaves for Intelligent Mobility (ICMIM)*, pp. 1–4, 2019.

[7] M. Barjenbruch *et al.*, "Interference detection and cancellation for automotive radar using time-frequency analysis," *IEEE MTT-S International Conference on Microwaves for Intelligent Mobility (ICMIM)*, pp. 1–4, 2015.

[8] X. Liu *et al.*, "IRNet: Interference recognition networks for automotive radars via autocorrelation features," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 4, pp. 2646–2658, Apr. 2021.

[9] J. Wang, M. Ding, and A. Yarovoy, "Interference mitigation for FMCW radar with sparse and low-rank Hankel matrix decomposition," *IEEE Transactions on Signal Processing*, vol. 70, pp. 822–834, 2022.