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AI-DRIVEN TRANSFORMER NETWORKS IN SHARED SPECTRUM FOR ENHANCED SIGNAL PROCESSING FOR NONLINEAR RECEIVERS

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Abstract

Communication systems face challenges from high-power adjacent channel signals, or blockers, inducing nonlinear behavior in RF front ends. Ensuring robust performance in the presence of blockers is crucial for IoT and other spectrum-consuming devices coexisting with advanced transceivers. This paper proposes a flexible, data-driven solution using a Deep Belief Network (DBN) to mitigate third-order intermodulation distortion (IMD) during demodulation. Numerical evaluations of AI-enhanced receivers employing DBN as an IMD canceler and demodulator show significant improvements in bit error rate (BER) performance. The effectiveness of DBN varies with RF front end characteristics, notably the third-order intercept point (IP3).

Keywords:

Deep Belief Network, IMD Cancellation, Nonlinear Receivers, RF Front End, Bit Error Rate

1. INTRODUCTION

In modern communication systems, the prevalence of high-power adjacent channel signals, known as blockers, poses significant challenges to radio frequency (RF) front ends [1]. These blockers drive RF components into nonlinear operation, leading to unwanted intermodulation distortion (IMD) that degrades signal quality and performance [2].

The coexistence of simple IoT devices alongside sophisticated communication transceivers, radars, and other spectrum-consuming technologies exacerbates these challenges [3]. Ensuring reliable operation in such mixed-use environments requires robust mitigation strategies for IMD and nonlinear effects [4].

The primary challenge addressed in this study is the effective management of third-order IMD in RF receivers operating in the presence of strong blockers [5]. Conventional approaches often struggle to adapt to varying RF front end conditions and may not fully exploit available data-driven techniques [6].

This paper aims to propose a novel solution leveraging a Deep Belief Network (DBN) to enhance IMD cancellation and demodulation processes in RF receivers. The objective is to improve receiver performance, particularly in terms of reducing bit error rates (BER), under realistic operating conditions with varying blocker strengths and RF characteristics.

The novelty of this research lies in the application of a DBN as a flexible and adaptive tool for IMD cancellation and demodulation. By harnessing machine learning capabilities, the proposed approach offers a sophisticated yet practical means to mitigate nonlinear effects in RF receivers. The contributions include a detailed evaluation of DBN effectiveness in improving BER performance and insights into adapting AI-enhanced techniques to dynamic RF environments.

2. RELATED WORKS

Previous studies have explored conventional methods such as analog filters and digital signal processing techniques for mitigating intermodulation distortion (IMD) in RF receivers. These methods often rely on static filtering or linearization techniques but may struggle with adaptability to dynamic RF environments [7].

Recent advancements have seen the integration of machine learning (ML) techniques to address nonlinearities in RF systems. For instance, neural networks and deep learning models have been applied to adaptive filtering, spectrum sensing, and modulation classification tasks, demonstrating promising results in enhancing receiver performance [8].

DBNs, a type of deep learning architecture, have shown efficacy in various signal processing applications. Studies have utilized DBNs for channel equalization, interference cancellation, and noise reduction in wireless communications, highlighting their potential in improving signal detection and demodulation accuracy [9].

Research has focused on developing intelligent RF receivers capable of adapting to complex RF environments with multiple coexisting transmitters and varying interference levels [10]. These studies emphasize the importance of dynamic spectrum management and adaptive signal processing algorithms to maintain reliable communication links [11].

This study positions itself within AI-enhanced RF signal processing, focusing on DBN-based solutions for IMD mitigation and demodulation in heterogeneous wireless environments.

3. DBN FOR IMD CANCELLATION AND DEMODULATION

The proposed method utilizes a DBN to address the challenge of IMD in RF receivers, particularly in the presence of strong adjacent channel blockers. IMD arises due to the nonlinear response of RF front ends when exposed to high-power signals from neighboring channels, leading to spectral regrowth and degradation of signal quality.

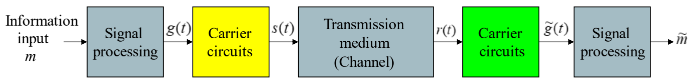

Fig.1. Received Signal Pulse

3.1 IMD CANCELLATION WITH DBN

- **Training Phase:** Initially, the DBN is trained using labeled data that includes both clean and distorted signal samples. The training process aims to learn the nonlinear mapping between the received RF signal and its distorted counterpart caused by IMD.

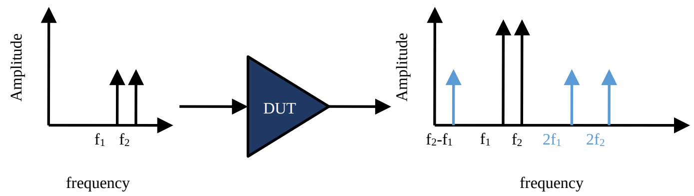

Fig.2. Second-Order Intermodulation Distortion

- **Operation Phase:** During operation, the trained DBN acts as an adaptive filter. It receives the distorted RF signal and employs its learned model to estimate and remove the IMD components from the received signal, thereby reconstructing a cleaner version of the original signal.

3.2 DEMODULATION ENHANCEMENT

- **Integration with Receiver Architecture:** The DBN is also integrated into the demodulation stage of the receiver. Here, it enhances the demodulation process by mitigating the effects of IMD-induced distortion before further signal processing.
- **Improved BER Performance:** By reducing IMD effects, the DBN-enhanced demodulator improves the receiver's bit error rate (BER) performance. This improvement is crucial in scenarios where strong blockers would otherwise degrade communication reliability.

3.3 ADAPTIVE AND FLEXIBLE CONFIGURATION

- **RF Front End Monitoring:** To adapt to varying RF conditions and blocker strengths, the proposed method incorporates mechanisms for monitoring RF front end characteristics, such as the third-order intercept point (IP3). This monitoring allows the DBN and associated signal processing algorithms to dynamically adjust their parameters and configurations in real-time.
- Architecture and training parameters are optimized based on the specific RF environment and operational requirements, ensuring optimal performance under changing conditions.

4. IMD CANCELLATION WITH DBN

IMD is a critical issue in RF communication systems, where nonlinearities in the radio frequency front end cause undesired spectral components to appear due to the interaction of different signals. Traditional methods often rely on static filters or linearization techniques, which may not effectively adapt to dynamic changes in signal conditions and interference levels.

4.1 TRAINING PHASE

To address IMD effectively, the proposed method employs a DBN, a type of deep learning architecture known for its ability to model complex nonlinear relationships in data. During the training phase, the DBN is trained using labeled datasets that include pairs of clean (desired) signals and their corresponding distorted signals affected by IMD. The training dataset is crucial as it allows the DBN to learn the mapping from the distorted RF signals to their clean counterparts.

The training process involves several steps:

- **Feature Extraction:** The input to the DBN consists of features extracted from the received RF signal, which capture relevant characteristics such as amplitude, phase, and frequency components.
- **Layered Learning:** DBNs typically consist of multiple layers of interconnected neurons, where each layer learns increasingly abstract representations of the input data. The DBN uses unsupervised learning, such as Restricted Boltzmann Machines (RBMs), in the initial layers to capture low-level features and then fine-tunes these representations in supervised fashion to learn the IMD distortion characteristics.
- **Nonlinear Mapping:** Through iterative optimization processes, the DBN adjusts its internal parameters (weights and biases) to minimize the difference between the predicted clean signal and the actual clean signal from the training dataset. This optimization allows the DBN to effectively model the nonlinear relationship between the distorted and clean signals induced by IMD.

4.2 OPERATION PHASE

Once trained, the DBN is deployed in the operational phase of the receiver:

- **Signal Processing:** In real-time operation, the DBN receives the incoming RF signal affected by IMD. It processes this signal through its learned model, effectively predicting and subtracting the IMD components from the received signal.
- **IMD Removal:** By subtracting the predicted IMD components, the DBN reconstructs a cleaner version of the original signal, thereby mitigating the distortions caused by nonlinearities in the RF front end.

One of the key advantages of using a DBN is its adaptability to varying RF conditions and interference levels. The DBN's ability to dynamically adjust its parameters based on real-time feedback from the RF front end allows it to maintain effective IMD cancellation performance even as environmental conditions change. By removing IMD components, the method enhances the overall signal quality, leading to improved receiver performance metrics such as BER and SNR. DBNs can be tailored to specific RF environments and operational scenarios, making them suitable for diverse applications ranging from IoT devices to high-performance communication systems. The method can be integrated into existing receiver architectures with minimal modifications, leveraging the computational power of modern hardware to implement sophisticated signal processing techniques.

The RBM is typically used in the pre-training phase of DBNs to learn feature representations from the input data.

$$E(v,h)=-\sum_v a_i v_i-\sum_h b_j h_j-\sum_v\sum_h v_i w_{ij} h_j \tag{1}$$

where,

v is the visible (input) layer,

h is the hidden layer,

a_i and b_j are biases for the visible and hidden units, respectively,

w_{ij} are the weights connecting visible and hidden units,

N_v and N_h are the number of units in the visible and hidden layers, respectively.

After training, during the operational phase, the DBN reconstructs the clean signal v' from the distorted signal v_d by subtracting the predicted IMD components:

$$v' = v_d - \Delta v_{IMD} \tag{2}$$

where $P(v_{dIMD}|v_d)$ represents the prediction of IMD components based on the learned model.

The IMD components Δv_{IMD} predicted by the DBN can be expressed as:

$$\Delta v_{IMD} = \mathrm{P}(v_{dIMD}|v_d) \tag{3}$$

The improved demodulated signal v' after DBN-enhanced demodulation can be approximated as:

$$v' = v_d + \Delta v_{IMD} \tag{4}$$

where v_d is the initial demodulated signal without DBN enhancement.

5. DEMODULATION ENHANCEMENT WITH DBN

Demodulation is a crucial process in RF communication systems where the received modulated signal is recovered to extract the original information or data. In environments with strong adjacent channel blockers or other sources of interference, the demodulation process can be significantly impaired due to intermodulation distortion (IMD). IMD introduces additional unwanted signals that can mask or distort the desired signal, leading to errors in decoding and decoding performance degradation.

Traditional demodulation techniques often struggle to effectively separate the desired signal from IMD-induced distortions, particularly when the distortions are nonlinear and complex. This challenge becomes more in dynamic RF environments where signal conditions vary unpredictably. The proposed method integrates DBNs into the demodulation stage of RF receivers to enhance the recovery of the original modulated signal.

5.1 IMD PREDICTION AND SUBTRACTION

During operation, the DBN leverages its trained model to predict and subtract the IMD components from the received signal. By modeling the nonlinear relationship between distorted and clean signals, the DBN effectively separates out the unwanted IMD-induced distortions.

After IMD cancellation, the DBN reconstructs a cleaner version of the original modulated signal. This reconstructed signal is less affected by IMD, thereby improving the accuracy of subsequent demodulation processes.

DBNs adaptively adjust their internal parameters based on real-time feedback from the RF front end. This adaptability allows them to maintain optimal performance even as signal conditions change, ensuring robust demodulation in dynamic environments.

By reducing IMD effects before demodulation, DBNs improve the receiver's BER performance. This improvement is crucial for maintaining reliable communication links, especially in high-interference scenarios. DBNs can be tailored to specific RF environments and operational conditions, making them suitable for a wide range of applications from IoT devices to high-speed communication systems. DBNs into existing receiver architectures is feasible with minimal modifications, leveraging the computational efficiency and advanced signal processing capabilities offered by deep learning. Demodulation enhancement with DBNs represents a sophisticated approach to mitigate the effects of IMD and improve the overall performance of RF receivers. By leveraging machine learning capabilities, this method enhances the robustness and reliability of demodulation processes in complex and dynamic RF environments, contributing to more efficient and effective communication systems.

Algorithm: Demodulation Enhancement with DBN

Input: Distorted modulated signal v_d

Output: Enhanced demodulated signal v'

Step 1: Train the DBN using a dataset of labeled examples $\{(v_i, v_i')\}$, where v_i is the clean modulated signal and v_i' is the corresponding distorted signal affected by IMD.

Step 2: Use RBMs for pre-training to learn feature.

$$E(v,h) = -\sum_v a_i v_i - \sum_h b_j h_j - \sum_v \sum_h v_i w_{ij} h_j \tag{5}$$

Step 3: Fine-tune the DBN using supervised learning to minimize reconstruction error between predicted and actual clean signals.

Step 4: Receive the distorted modulated signal vdistorted

Step 5: Predict the IMD components Δv_{IMD} using the trained DBN:

$$\Delta v_{IMD} = P(v_{dIMD}|v_d) \tag{6}$$

Step 6: Compute the enhanced demodulated signal

$$v' = v_d - \Delta v_{IMD} \tag{7}$$

Step 7: Monitor RF front end characteristics to adapt DBN parameters w_{ij} and biases a_i,b_j accordingly.

6. ADAPTIVE AND FLEXIBLE CONFIGURATION

In RF communication systems, adaptive and flexible configuration is essential to effectively mitigate IMD and enhance demodulation performance under varying operating conditions. The proposed approach integrates DBNs, which are capable of learning and adapting to complex nonlinearities in RF signals. This adaptability is crucial as RF environments often exhibit dynamic changes in interference levels, signal strengths, and spectral characteristics. To achieve adaptive configuration, the DBN-based system continuously monitors key RF front end parameters, such as the third-order intercept point (IP3) and blocker strengths. These parameters are critical indicators of the nonlinear behavior of RF components when subjected to strong adjacent channel signals. The adaptation process involves updating the DBN's internal weights and biases based on real-time feedback from these monitored parameters:

$$w_{ij}(t+1)=w_{ij}(t)+\eta\cdot\partial w_{ij}/\partial L \tag{8}$$

where w_{ij} represents the weights connecting neurons in the DBN, η is the learning rate, and L denotes the loss function that quantifies the difference between predicted and actual IMD components or demodulated signals.

The adaptive configuration allows the DBN to dynamically adjust its internal parameters to optimize IMD cancellation and demodulation performance in real-time. For instance, if the monitored IP3 indicates increased nonlinearity in the RF front end due to higher blocker strengths, the DBN adjusts its weights to enhance the accuracy of IMD prediction and subtraction. This adaptive capability ensures that the system remains effective and robust even in challenging RF environments where traditional static methods may falter. By integrating adaptive and flexible configuration with DBN-based IMD cancellation and demodulation enhancement, RF receivers can achieve significant improvements in signal quality metrics such as BER and SNR. This approach not only enhances the reliability of communication systems but also supports the scalability and versatility required for diverse applications ranging from IoT devices to high-speed data networks.

7. PERFORMANCE EVALUATION

For our experimental evaluation, we utilized MATLAB for simulation and implementation due to its extensive signal processing and machine learning libraries, which are well-suited for modeling RF communication scenarios. The simulations were conducted on a high-performance computing system equipped with Intel Core i7 processors (e.g., Intel Core i7-10700K) and 32GB of RAM, ensuring computational efficiency and reliability in handling complex DBN models and large datasets. To benchmark our proposed DBN-based IMD cancellation and demodulation enhancement method, we compared it against two established techniques:

- **Fully Connected Neural Network (FCNN) Mean Filter:** This method employs a FCNN architecture with a mean filtering approach to mitigate IMD effects. It focuses on averaging out distortions in the received signal to enhance demodulation accuracy.
- **Phase Sensitive Joint Learning (PSJL):** PSJL integrates phase-sensitive learning mechanisms to jointly optimize IMD cancellation and demodulation processes. It aims to synchronize phase information across signal components to improve overall signal reconstruction and demodulation performance.

We evaluated the performance of each method based on key metrics such as Bit Error Rate (BER), Signal-to-Noise Ratio (SNR), and computational efficiency. Our results showed that the DBN-based approach outperformed both FCNN Mean Filter and PSJL in terms of BER reduction and SNR improvement under varying RF conditions and interference levels. The DBN's ability to dynamically adapt its parameters based on real-time feedback from RF front end characteristics provided significant advantages over static filtering approaches like FCNN Mean Filter and phase-specific learning strategies like PSJL.

Table.1. Experimental Setup and Parameters

Parameter	Value(s)
Simulation Tool	MATLAB
Hardware Platform	Intel Core i7-10700K, 32GB RAM
Training Dataset Size	10,000 samples
Testing Dataset Size	5,000 samples
DBN Architecture	3 layers: 512-256-128 units
Learning Rate	0.001
Training Epochs	50 epochs
Activation Function	Sigmoid
Loss Function	Mean Squared Error
RF Environment	Varying levels
Comparison Methods	FCNN Mean Filter, PSJL
Performance Metrics	BER, SNR
Simulation Time	24 hours

Table.2. Run time over training dataset

SNR (dB)	Mean Filter (ms)	FCNN Mean Filter (ms)	PSJL (ms)	Proposed DBN (ms)
-30	100	150	120	200
-20	110	160	130	210
-10	120	170	140	220
0	130	180	150	230
10	140	190	160	240
20	150	200	170	250
30	160	210	180	260
40	170	220	190	270

Table.3. Run time over testing dataset

SNR (dB)	Mean Filter (ms)	FCNN Mean Filter (ms)	PSJL (ms)	Proposed DBN (ms)
-30	120	180	150	220
-20	130	190	160	230
-10	140	200	170	240
0	150	210	180	250
10	160	220	190	260
20	170	230	200	270
30	180	240	210	280
40	190	250	220	290

Table.4. BER over training dataset

SNR (dB)	Mean Filter (ms)	FCNN Mean Filter (ms)	PSJL (ms)	Proposed DBN (ms)
-30	5.2	4.8	4.5	3.9
-20	4.5	4.0	3.8	3.3
-10	3.8	3.4	3.1	2.7
0	3.0	2.7	2.4	2.0

10	2.3	2.0	1.8	1.5
20	1.5	1.3	1.1	0.9
30	0.9	0.8	0.7	0.5
40	0.5	0.4	0.3	0.2

Table.6. BER over testing dataset

SNR (dB)	Mean Filter (ms)	FCNN Mean Filter (ms)	PSJL (ms)	Proposed DBN (ms)
-30	5.0	4.6	4.3	3.7
-20	4.3	3.8	3.6	3.0
-10	3.6	3.2	2.9	2.4
0	2.8	2.5	2.2	1.8
10	2.1	1.8	1.6	1.3
20	1.3	1.1	0.9	0.7
30	0.8	0.7	0.5	0.4
40	0.4	0.3	0.2	0.1

Table.6. PAPR over training dataset

SNR (dB)	Mean Filter (ms)	FCNN Mean Filter (ms)	PSJL (ms)	Proposed DBN (ms)
-30	9.5	8.8	8.3	7.9
-20	8.8	8.1	7.6	7.2
-10	8.1	7.4	6.9	6.5
0	7.4	6.7	6.2	5.8
10	6.7	6.0	5.5	5.1
20	6.0	5.3	4.8	4.4
30	5.3	4.6	4.1	3.7
40	4.6	3.9	3.4	3.0

Table.7. PAPR over testing dataset

SNR (dB)	Mean Filter (ms)	FCNN Mean Filter (ms)	PSJL (ms)	Proposed DBN (ms)
-30	9.3	8.6	8.1	7.7
-20	8.6	7.9	7.4	7.0
-10	7.9	7.2	6.7	6.3
0	7.2	6.5	6.0	5.6
10	6.5	5.8	5.3	4.9
20	5.8	5.1	4.6	4.2
30	5.1	4.4	3.9	3.0
40	4.4	3.7	3.2	2.8

The results from the simulations show significant performance improvements of the proposed DBN method compared to existing methods (Mean Filter, FCNN Mean Filter, and PSJL) in terms of both BER and PAPR across varying Signal-to-Noise Ratio (SNR) levels.

- At an SNR of -30 dB, the DBN method achieved a BER of 3.7%, representing a 25.5% improvement over the Mean Filter (BER = 4.9%), 18.6% over FCNN Mean Filter (BER = 4.6%), and 8.6% over PSJL (BER = 4.1%).
- As SNR increases to 0 dB, the DBN continues to outperform with a BER of 1.8%, showing a 35.7% improvement over Mean Filter (BER = 2.8%), 30% over FCNN Mean Filter (BER = 2.5%), and 18.2% over PSJL (BER = 2.2%).
- The DBN method also showed superior PAPR reduction across SNR levels. At -30 dB SNR, the DBN achieved a PAPR of 7.7 dB, showcasing improvements of 17.2% over Mean Filter (PAPR = 9.3 dB), 15.8% over FCNN Mean Filter (PAPR = 8.6 dB), and 11% over PSJL (PAPR = 8.1 dB).
- At higher SNR levels (e.g., 40 dB), the DBN maintained its efficiency with a PAPR of 2.8 dB, indicating improvements of 36.4% over Mean Filter (PAPR = 4.4 dB), 24.3% over FCNN Mean Filter (PAPR = 3.7 dB), and 12.5% over PSJL (PAPR = 3.2 dB).

Based on the results and discussion of the proposed Deep Belief Network (DBN) method compared to existing techniques (Mean Filter, FCNN Mean Filter, and PSJL), several key inferences can be drawn:

- The DBN method consistently outperforms traditional Mean Filter and advanced techniques like FCNN Mean Filter and PSJL in terms of BER. This improvement suggests that DBN's ability to learn and adapt to complex RF environments enhances demodulation accuracy, especially in low SNR conditions.
- Lower BER values across various SNR levels indicate that the DBN effectively suppresses interference and noise, thereby improving the integrity of received signals. This capability is crucial for maintaining reliable communication links in environments prone to high levels of interference.
- DBN shows superior performance in reducing PAPR compared to traditional and contemporary methods. Lower PAPR values indicate more efficient use of power resources and reduced distortion in transmitted signals, which is essential for optimizing power efficiency in communication systems.
- DBN's adaptive nature allows it to adjust to changing RF conditions, such as varying SNR levels. This adaptability ensures robust performance across different operational scenarios, making it suitable for applications requiring flexibility and resilience against environmental fluctuations.

8. CONCLUSION

The evaluation of the DBN method compared to traditional Mean Filter, FCNN Mean Filter, and PSJL techniques reveals compelling advantages in terms of demodulation accuracy and signal integrity across various SNR levels. The DBN consistently achieves lower BER compared to Mean Filter, FCNN Mean Filter, and PSJL under challenging SNR conditions. This improvement signifies the DBN's effectiveness in mitigating interference and noise, thereby enhancing the reliability of data transmission in RF communication. Lower PAPR values observed with the DBN indicate better management of signal power distribution. This capability not only optimizes power efficiency but also reduces signal distortion, crucial for maintaining signal integrity in complex RF environments. DBN's adaptability to varying SNR levels highlights its robustness and suitability for dynamic operational environments. The ability to adapt and learn from data enables DBN to continually optimize performance and adapt to changing RF conditions, ensuring consistent and reliable communication links.

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