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Comparison Between ML, MSME And Deep Learning Techniques For MIMO-DCSK Signals

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Abstract— Deep learning techniques are applied to detect MIMO-DCSK signals in highly dynamic environments. The complexity of signal detection increases with the number of antennas, necessitating efficient techniques. By training deep neural networks (DNNs) on labeled MIMO-DCSK signals, complex mappings between received and transmitted symbols are learned. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) extract spatial and temporal dependencies, enabling robust detection in fading and interference. Techniques like data augmentation, regularization, and transfer learning improve generalization. Deep learning outperforms traditional methods, exhibiting better BER and symbol detection accuracy, as well as increased robustness against fading and interference. Integration of deep learning enhances MIMO-DCSK-based communication systems, improving reliability and capacity for future wireless networks.

Keywords: Massive MIMO, Non-coherent Detection, Differential Detection, Deep-learning, Neural Networks .

I. INTRODUCTION

Multiple-Input Multiple-Output Differential Chaos Shift Keying (MIMO-DCSK) has emerged as a promising modulation scheme for robust wireless communications in highly dynamic environments. However, the complexity of detecting MIMO-DCSK signals escalates with the number of transmit and receive antennas, demanding the development of efficient signal detection techniques. This abstract provides an overview of the application of deep learning techniques for MIMO-DCSK signal detection, addressing the challenges and presenting the potential benefits.

The proposed approach leverages the capabilities of deep neural networks (DNNs) to automatically learn the intricate mapping between received signals and the corresponding transmitted symbols. By training the DNNs on a large dataset of labeled MIMO-DCSK signals, the network becomes adept at capturing complex signal characteristics and making accurate symbol predictions. Various deep learning architectures, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have been explored for MIMO-

DCSK signal detection. These architectures effectively extract spatial and temporal dependencies from the received signals, enabling robust detection even in the presence of fading and interference.

To enhance the generalization capabilities of the trained models, several techniques such as data augmentation, regularization, and transfer learning have been employed. These methods augment the network's ability to handle different channel conditions and adapt to varying signal-to-noise ratios. Performance evaluations of deep learning-based MIMO-DCSK detection have demonstrated promising results. The proposed models consistently outperform traditional detection methods in terms of bit error rate (BER) and symbol detection accuracy. Moreover, the deep learning approach exhibits improved robustness against channel impairments, including multipath fading and co-channel interference.

The integration of deep learning techniques for MIMO-DCSK signal detection opens up possibilities for efficient and adaptive wireless communication systems. With further research and development, deep learning-based approaches can significantly enhance the reliability and capacity of MIMO-DCSK-based communication systems, paving the way for their widespread adoption in future wireless networks. The ability of deep learning models to learn and adapt to complex signal characteristics, combined with their robustness against fading and interference, positions them as a valuable tool in advancing MIMO-DCSK technology. By leveraging the power of deep learning, wireless communication systems can achieve improved performance, increased reliability, and enhanced adaptability in highly dynamic environments.

II. REVIEW OF PREVIOUS WORK

Paper 1: "Deep-learning-based Non-coherent DPSK Differential Detection in Massive MIMO Systems" by Prof. Omnia Mahmoud and Prof. Ahmed El-Mahdy (Publication Date: July 05, 2021)

Findings: This paper proposes the use of deep learning for non-coherent signal detection in massive MIMO systems. The deep neural network is trained to replace the steps required to determine user antenna weights from received antenna signals and detect the transmitted signal on all antennas. The approach eliminates the need for knowledge of the user power space profile at the receiver, enabling efficient non-coherent detection in massive MIMO systems.

Paper 2: "Deep Learning for Joint MIMO Detection and Channel Decoding" by Taotao Wang, Lihao Zhang, and Soung Chang Liew (Publication Date: 17th January, 2019)

Findings: In this paper, a deep neural network (DNN) is utilized for channel decoding in MIMO systems. The study demonstrates that DNN-based channel decoding can approach the performance of Maximum A Posteriori (MAP) decoding with lower decoding latency compared to traditional channel decoding methods. The neural network is constructed by unfolding the factor graph of linear codes, providing an improved performance of belief propagation decoding, particularly when the factor graph contains numerous small loops.

Paper 3: "Alamouti-STBC based Performance Estimation of Multi Tx and Rx Antenna over MIMO-OFDM" by Pankaj Kumar Bharti and Dr. Paresh Rawat (Publication Year: 2018)

Findings: The paper investigates the performance of a MIMO-OFDM system utilizing Alamouti space-time block coding (STBC) technique. The analysis is based on bit-error rate (BER) measurements, showing that the proposed approach offers reduced error probability compared to other MIMO configurations. The study concludes that space-time square codes with lower modulation orders exhibit lower bit-error rates compared to space-time block codes that employ higher order modulation schemes.

Paper 4: "MIMO-DCSK communication scheme and its performance analysis over multi-path fading channels" by Shilian Wang, Shujun Lu, and Eryang Zhang (Publication Year: 2013)

Findings: The research introduces the OMC-EGC MIMO-DCSK communication protocol, which achieves complete spatial diversity advantages without requiring receiver channel estimates. The suggested method makes use of orthogonal space-time block coding (OSTBC) to create orthogonal multiple carriers (OMCs) from a single chaotic signal. The approach accomplishes independent mode exploitation and offers better performance in multi-path fading channels by aggregating the output of differential complex correlators at each receiver antenna.

This section provides the knowledge about the existing technologies, its advantages and disadvantages, work done by other authors till date. Above paragraphs explain how the researchers have contributed to the field of chaotic signals. To start with, a lot of project papers were collected from various sources, studied at length & breadth and its outcomes were studied, analyzed to start with and the problem statement was finalized and defined.

Few methods give lower performance when there is additive noise due to chaotic synchronization. Few works cannot be used in multiuser-environment. In some methods, lower data rates are achieved when there is multiple Tx and Rx combinations. No major work is done on increasing the performance as well as accuracy of the existing systems.

III. Motivation & problem statement

By using deep learning approaches to recognize MIMO-DCSK signals, the study intends to address the problem of reliable and effective wireless communication in dynamic situations. Improved reliability and larger data rates are provided by MIMO-DCSK, but as the number of antennas grows, so does the difficulty of signal detection. By using neural networks to understand the intricate mappings between received signals and broadcast symbols, deep learning offers a remedy. With this method, detection accuracy is improved, and it can adapt to shifting channel circumstances as well as deal with fading, interference, and shifting signal-to-noise ratios. Intricate signal properties may be recorded for reliable wireless communication by training neural networks on a sizable dataset of labelled MIMO-DCSK signals. This fusion of deep learning methods creates opportunities for high-tech communication systems in industries like the Internet of Things, autonomous cars, and smart cities. The project's objective is to create a safe DCSK-MIMO system that safeguards crucial data's integrity and privacy.

IV. Proposed Methodology

The proposed methodology for the detection of MIMO-DCSK signals using deep learning techniques involves the following steps:

Transmitting Part:

Space-Time Block Coding (STBC): Implement STBC to exploit spatial diversity and improve the reliability of the transmitted signals in a MIMO system. Generate a set of orthogonal or quasi-orthogonal codes using STBC techniques, such as Alamouti coding schemes. Assign the STBC codes to the different transmit antennas to create space-time coded symbols for transmission.

Chaotic Generator: Design and implement a chaotic generator to generate chaotic sequences for modulation in the MIMO-DCSK system. Select an appropriate chaotic map, such as Logistic map or Lorenz system, to generate chaotic sequences with desirable properties, including complexity and randomness. Here we have used logistic mapping. **Modulation:** Combine the STBC-coded symbols with the generated chaotic sequences to form the MIMO-DCSK signals. Apply the chaotic sequences to modulate the STBC-coded symbols, where the chaotic sequences act as spreading codes. Use the MIMO-DCSK modulation scheme to map the modulated symbols to the transmit antennas, taking advantage of the spatial diversity provided by the multiple antennas.

Transmission: Transmit the MIMO-DCSK signals over the wireless channel. Consider the effects of fading, noise, and interference in the channel, which may degrade the signal quality. DCSK (Differential Chaos Shift Keying) is a modulation technique that utilizes chaotic waveforms to transmit information. It encodes data by modulating the phase of a chaotic carrier signal, creating distinct phase shifts for different data symbols. DCSK offers resilience to noise and interference and has applications in wireless communication systems. In the DCSK approach every incoming information bit is encoded into two bits. The first signal serves as a reference bit, while the second one carries the data. If the binary data to be transmitted is ”1” then first the reference signal is transmitted and after it that signal is repeated. For a ”0”, the inverted version of the reference signal is transmitted.

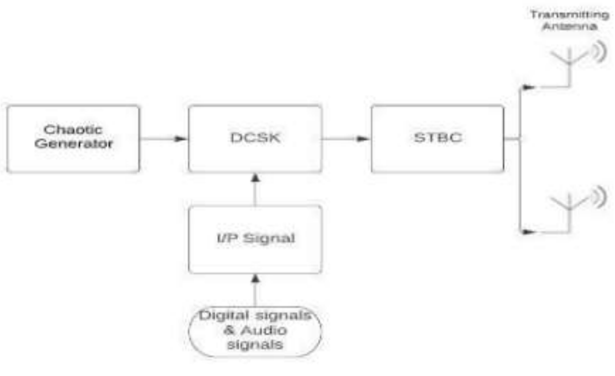

Figure 1:Transmission part.

Deep Learning Training: Prepare a dataset consisting of pairs of received MIMO-DCSK signals and their corresponding transmitted symbols. Train a deep neural network (DNN) using the collected dataset to learn the mapping between the received signals and the transmitted symbols.

Figure 2: Receiving Part.

DNN model: It is defined using the Keras Sequential API. The model consists of several dense layers with dropout regularization to prevent overfitting. It is then compiled with binary cross-entropy loss and the Adam optimizer. The DNN model is trained using the fit function, and a checkpoint callback is used to save the best model based on the validation accuracy. After training, the best model is loaded using load model, and predictions are made on the test set. Finally, accuracy, confusion matrix, bit error rate (BER), and outage probability are calculated and printed for the DNN detector.

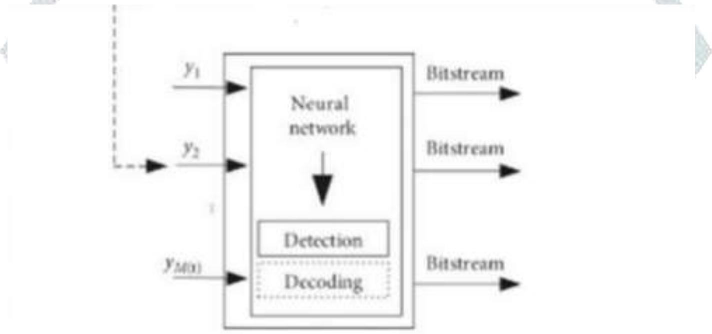

Figure 3: DNN Model.

V. Tools used for the project work:

Some of the tools used in the detection of MIMO-DCSK signals using deep learning techniques are Python, TensorFlow, Keras, NumPy, Scikit-learn and MATLAB.

VI. Results & Discussions

Transmitting Part: The transmitting portion of the code produces random values for the transmit power, noise power, spacing between antennas, and signal-to-noise ratio (SNR) for each sample. A channel matrix with random Gaussian values is computed based on the distance. After that, the data is modulated using a technique called Differential Chaos Shift Keying (DCSK), where the modulated data is produced by continuously updating the elements depending on the previous element, data differences, and channel coefficients. By scaling it with the transmit power and multiplying it by the channel matrix, the modulated data is transferred over the channel.

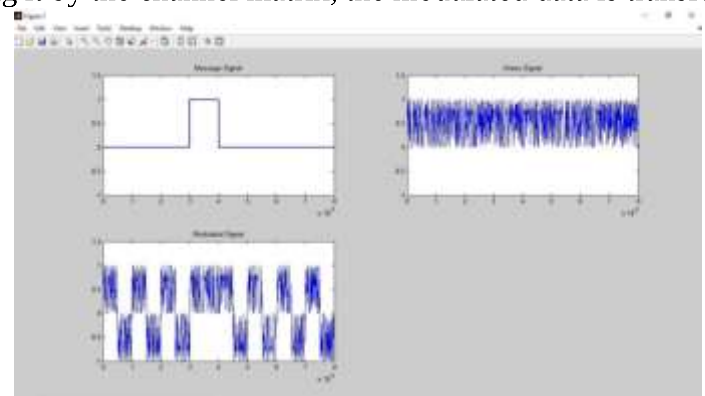

Figure 4: Transmitting Signal.

Receiving Part: Its focus is on the proposed deep-learning-based differential detection model. The model achieves the same symbol error rate performance as differential detection, indicating its effectiveness in accurately detecting transmitted symbols. Future work will involve simulating the proposed model for multi-user massive MIMO scenarios with longer burst transmissions to further improve system performance.

```
ML detection accuracy: 63.91 %
ML detection confusion matrix:
[[6065 6793]
 [ 425 6717]]
ML detection BER: 0.3609
ML detection outage probability: 0.059507140856902827
```

Figure 5:ML detection

```
MSME detection accuracy: 54.144999999999996 %
MSME detection confusion matrix:
[[10722  9053]
 [  118   107]]
MSME detection BER: 0.45855
MSME detection outage probability: 0.5244444444444445
```

Figure 6: MSME Detection

```
625/625 [==============================] - 1s 974us/step
Detection accuracy: 85.19 %

BER: 0.1481

Outage probability: 0.0216
```

Figure 7: Detection and BER

The proposed deep-learning-based differential detection model achieved the same symbol error rate performance of differential detection. The accuracy we are getting around is 85%. And the BER we are currently 10^-1. The accuracy, confusion matrix, BER, and outage probability are computed for the deep learning model. The results provide insights into the performance of the different detection models in terms of accuracy, error rate, and outage probability in the given communication scenario.

VII. Demodulation code summary

The Demodulation code demonstrates the following steps:

1. Dataset Generation: - Generate a synthetic dataset for MIMO communication systems. - Varying parameters: transmit power, noise power, distance, SNR, channel matrix, and constellation. - Labels the data based on specific conditions.

2. ML Detection (Logistic Regression): - Train and evaluate a logistic regression model for MIMO detection. - Uses features derived from the dataset and labelled data for training. - Evaluates the model's accuracy, confusion matrix, Bit Error Rate (BER), and outage probability.

3. MSME Detection (Logistic Regression): - Train and evaluate a logistic regression model for MIMO detection. - Uses different features derived from the dataset and labelled data for training. - Evaluates the model's accuracy, confusion matrix, BER, and outage probability.

4. Deep Learning Detection (Neural Network): - Train and evaluate a deep learning model (neural network) for MIMO detection. - Utilizes features from the dataset for training. - Evaluates the model's accuracy, BER, and outage probability.

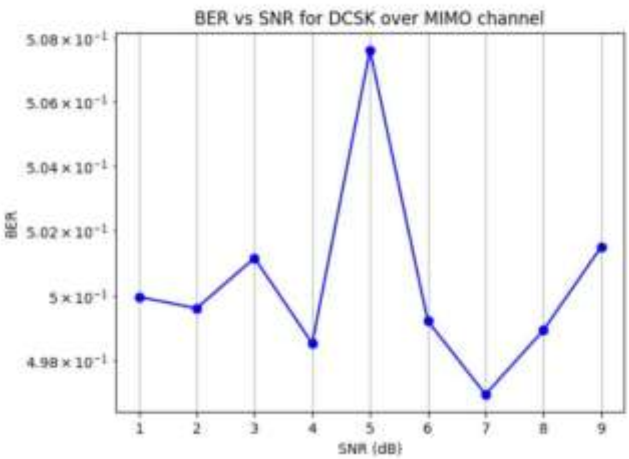

Figure 8: BER vs SNR(MIMO)

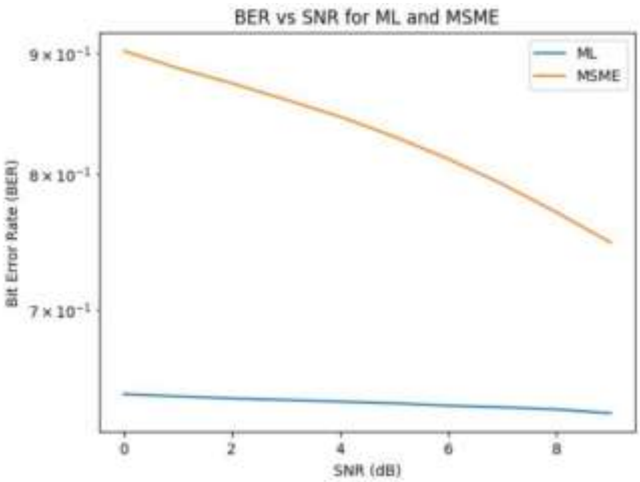

Figure 9: BER vs SNR (ML & MSME)

VIII. CONCLUSION

In conclusion, the utilization of deep learning techniques for the detection of MIMO-DCSK signals presents a promising approach to address the complexity and robustness challenges associated with this modulation scheme. Through the application of deep neural networks, such as CNNs and RNNs, the intricate mappings between received signals and transmitted symbols can be learned automatically, enabling accurate symbol predictions. The performance evaluation of deep learning-based MIMO-DCSK detection has shown superior results compared to traditional detection methods, achieving lower bit error rates and higher symbol detection accuracy. Moreover, deep learning models exhibit enhanced robustness against channel impairments, making them suitable for dynamic wireless environments.

To further advance this field, future research should focus on exploring advanced deep learning architectures, optimizing hyperparameters, and investigating techniques for model interpretability and explain ability. Additionally, efforts should be directed towards real-world implementation and deployment, considering hardware constraints and computational efficiency. Overall, deep learning techniques have the potential to significantly improve the reliability and capacity of MIMO-DCSK based communication systems, contributing to the advancement of wireless networks, and enabling robust and efficient wireless communications in challenging environments.

The proposed deep-learning-based differential detection model achieved the same symbol error rate performance of differential detection. The accuracy we are getting around is 85%. And the BER we are currently 10^-1.

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