Neural Network-Based Distributed Transmit Beamforming for UAV-to-Base Communications in Disaster Areas: Optimization and Adaptation Strategies

Fadi Hantouli
Department of Robotics and Mechatronics Engineering
Cognitive Robotics Lab
Kennesaw State University
Marietta, GA, USA
fhantoul@students.kennesaw.edu

Sumit Chakravarty
Department of Electrical and Computer Engineering
Cognitive Sensing and Communication Lab (CSCL)
Kennesaw State University
Marietta, GA, USA
schakra2@kennesaw.edu

David Guerra-Zubiaga
Department of Robotics and Mechatronics Engineering
Cognitive Robotics Lab
Kennesaw State University
Marietta, GA, USA
dguerraz@kennesaw.edu

Abstract

In disaster-stricken areas, rapid and reliable transmission of information is crucial for effective rescue and recovery operations. Traditional communication infrastructures often fail in such scenarios, necessitating alternative solutions. This position paper examines the deployment of a fleet of Unmanned Aerial Vehicles (UAVs) utilizing Distributed Transmit Beamforming (DTB) and Neural Networks (NN) for enhanced UAV-to-base communications. The UAVs are equipped with advanced sensors to collect real-time data transmitted to a central base station. NNs play a pivotal role in this system by facilitating synchronization among UAVs, ensuring the cybersecurity of data transmissions, and providing predictive analytics for the physical channel. The DTB technique enhances signal strength and reduces interference, ensuring highly reliable communication channels. The base station, equipped with powerful computing resources, analyzes the data to generate actionable insights, guiding rescue teams on the ground. This integrated approach improves the reliability and speed of data transmission and leverages NN algorithms for real-time analysis and decision-making, optimizing disaster response efforts.

CCS Concepts

• **Hardware → Robustness**; • **Networks → Cognitive radios**; • **Computing methodologies → Neural networks**.

Keywords

Neural Network (NN), Distributed Transmit Beamforming (DTB), UAVs, Cybersecurity, Channel Estimation, TV White Space (TVWS) Spectrum, Ground Station (GS), CNN.

1 Introduction

Natural disasters such as earthquakes, hurricanes, and floods can severely damage communication infrastructure, hindering rescue and recovery operations [1][2]. The immediate need for reliable communication channels to transmit real-time information to rescue teams and decision-makers is paramount [1]. This paper presents a solution using a fleet of Unmanned Aerial Vehicles (UAVs) equipped with Distributed Transmit Beamforming (DTB) technology to establish robust UAV-to-base communication networks. DTB enables multiple UAVs to coordinate their transmissions to create a focused beam, enhancing the signal strength and quality of the communication link between the UAVs and the base station. By leveraging neural networks (NN) for UAV synchronization and cybersecurity, this approach aims to improve the reliability and efficiency of the communication network in disaster-affected areas. The proposed system allows UAVs to share information, acknowledge messages, and update parameters based on predictions from NN algorithms, ensuring continuous and secure data transmission to support critical rescue operations.

2 UAV Fleet and DTB Technology

The UAVs are equipped with sensors such as cameras, thermal imaging, and LiDAR to gather comprehensive data from the disaster area Some examples. A paginated journal article [2][3]. These advanced sensors enable the UAVs to capture detailed information, including visual imagery, temperature variations, and 3D environmental mapping. The Distributed Transmit Beamforming (DTB) technique allows the UAVs to transmit this data collectively, forming a strong and focused signal directed towards the base station [4]. By coordinating their transmissions, the UAVs effectively create a virtual antenna array, which significantly reduces interference and enhances signal strength. This method ensures reliable communication channels between the UAV fleet and the base station, even in challenging environments where traditional communication infrastructure may be compromised. The DTB technology thus plays a crucial role in maintaining continuous and high-quality data transmission, which is essential for timely and effective disaster response [4][5].

3 Role of Neural Networks

Neural Networks are integral to the proposed system in three main areas:

- **Synchronization for Coherent Data Transmission:** Precise synchronization is essential for effective DTB, especially in dynamic environments. NNs predict optimal transmission timings using historical and real-time data, minimizing interference and maximizing signal strength [1]. During synchronization, UAVs share information and send acknowledgment messages to the base station. The base station responds with updated parameters, which UAVs use to adjust their transmission timings, ensuring effective data transmission back to the base station.

- **Cybersecurity Enhancement:** NNs enhance cybersecurity by detecting and mitigating cyber threats in real-time. They recognize normal communication patterns between UAVs and the base station, identifying deviations that may indicate potential cyber threats. Integrated into Intrusion Detection Systems (IDS), NNs use advanced learning techniques to spot and respond to sophisticated attacks, automating responses to minimize impact [1]. By enhancing encryption algorithms and validating data integrity, NNs ensure the confidentiality and accuracy of the data transmitted, protecting it from tampering or interception.
- **Predictive Analytics for Physical Channel:** NNs enhance DTB in UAV networks by predicting optimal parameters through predictive analytics for the physical communication channel. NNs leverage comprehensive data collected from the communication channel, including signal strength, noise levels, interference patterns, and UAV positions [4]. This dataset reveals critical patterns and relationships across various operational scenarios. NNs use current channel state information (CSI) from UAVs to dynamically predict optimal beamforming parameters, enabling adaptive adjustments to the beamforming strategy and enhancing signal quality and robustness.

4 Role Past Work: Channel Estimation NN Model for Predicting Clean Signals

Our previous research focused on developing a Convolutional Neural Network (CNN) model for channel estimation, specifically targeting the prediction of clean signals and channels in communication systems. Central to our approach was the design and implementation of a CNN architecture adept at learning and predicting channel characteristics from noisy input data. We curated comprehensive datasets encompassing varied channel conditions and utilized supervised learning techniques to train the model effectively.

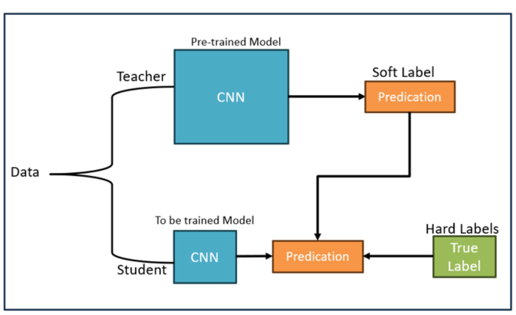

Figure 1: CNN Model - Student-Teacher Strategy.

To enhance the model's performance, we employed a student-teacher strategy, where a more complex teacher model guided the learning process of a simpler student model as illustrated in Figure 1. Through rigorous training and validation, the CNN was optimized to accurately estimate clean signals and channels based on observed noisy inputs, demonstrating its proficiency in handling complex, real-world scenarios.

5 Aspects of Investigation

Table 1 summarizes the key aspects, parameters, models/functions, and algorithms involved in our investigation.

Table 1: Aspect of Investigation

Aspect	Details
Parameters	Channel Conditions, Dataset Size, Data Augmentation, Signal-to-Noise Ratio (SNR), Preprocessing Steps, Filter Size, Number of Filters, Activation Functions, Loss Function, Optimization Algorithm, Learning Rate, Batch Size, Epochs, Validation Accuracy, Training Time, Computational Resources, Frameworks, Libraries, Environment
Models/Functions	CNN Architecture (number and types of layers), Teacher Model, Student Model, Activation Functions, Loss Function (MSE), Optimization Functions (Adam, SGD)
Algorithms	CNN Training, Knowledge Distillation, Data Augmentation

This work contributes valuable insights to the ongoing evolution of CNN-based approaches in wireless communication technologies, paving the way for future advancements in adaptive signal processing and system optimization strategies.

6 Five-Step Approach of the UAV-Ground Station Process Cycle

To illustrate the five-step approach of the process cycle, we can break down the steps along with the corresponding actions taken at the UAVs and the ground station (GS) as illustrated in Figure 2 and 3.

6.1 Pre-Flight Preparation (P1): Step 1

In the Pre-Flight Preparation (P1) phase, UAVs are stationed at a centralized charging station, where they undergo essential preparations before commencing their mission. This phase ensures that UAVs are equipped with the necessary information and resources to execute their tasks effectively. UAVs are charged, provided with updated trajectory data, synchronized, and undergo software and system checks as illustrated in Figure 2.

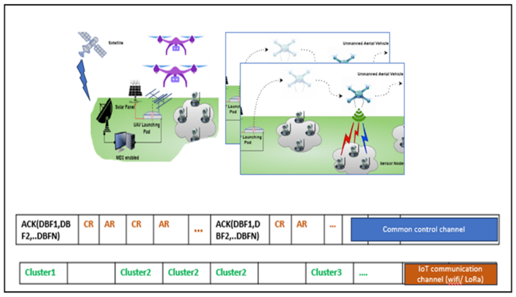

Figure 2: Flight Preparation and Deployment.

6.2 Initial Deployment and Setup: Step 2

Using dynamically updated trajectories, UAVs depart from the charging station and navigate to predetermined positions. Utilizing the TV White Space (TVWS) spectrum, UAVs establish essential communication links with the GS, including a control channel for command and coordination and a data channel for transmitting collected information. GS dynamically allocates TVWS frequencies, and as UAVs reach their designated positions, they send acknowledgment messages to the GS. The CNN at the GS processes the incoming data to predict crucial channel parameters, guiding the optimization of subsequent communication links.

6.3 CNN Model for Beamformers: Step 3

A CNN model generates beamformers for all UAVs, leveraging previous parameters from channel estimation processes and historical data. The CNN computes optimal beamformers for each UAV, ensuring collaborative beamforming and effective communication. Using a CNN model, the system minimizes interference, maximizes spectral efficiency, and ensures robust data transmission.

6.4 Data Transmission: Step 4

UAVs transmit data to the GS via the dedicated TVWS data channel, continuously adjusting their beamforming parameters based on GS feedback. The GS receives the data and sends acknowledgment messages and prediction parameters to refine UAV transmission settings, ensuring robust and efficient communication.

6.5 Post-Flight Analysis and Return: Step 5

Post-flight analysis is conducted at both the UAVs and the GS. UAVs analyze their performance using feedback received during the mission and adjust their trajectories and communication protocols for future flights. After completing tasks, UAVs return to the charging station. The GS comprehensively analyzes the received data and performance metrics, preparing detailed reports and updating protocols as illustrated in Figure 3. This phase is crucial for continuous improvement and ensuring the success of future deployments.

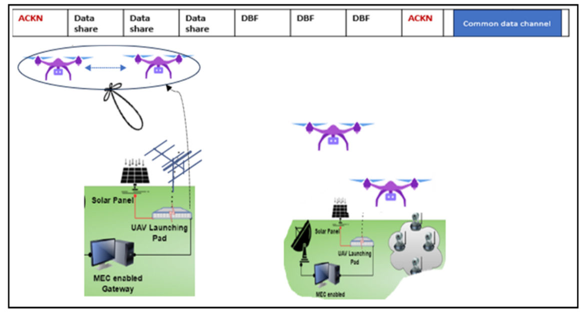

Figure 3: Post-Flight Analysis and Return.

7 Conclusion

The proposed system for disaster response involves using UAVs equipped with Distributed Transmit Beamforming (DTB) and Neural Networks (NNs) to maintain reliable communication channels in environments where traditional infrastructure is compromised. The UAVs use advanced sensors to collect and transmit real-time data, while DTB enhances signal strength and reduces interference. NNs ensure precise synchronization, enhance cybersecurity, and provide predictive analytics for optimizing communication. The system's five-step process—covering preparation, deployment, beamforming, data transmission, and post-flight analysis—demonstrates an efficient approach to managing UAV operations and data handling. This integrated solution represents a significant advancement in disaster communication, supporting timely and effective response efforts.

8 Future Work

Future work in this area will focus on refining the integration of UAVs equipped with advanced sensors and NNs for enhanced disaster response communication systems. Key objectives will include developing more robust NN algorithms to improve synchronization and collaboration among UAVs, leading to greater resilience against potential communication failures. Additionally, further research will be conducted to optimize the DTB technique, aiming to maximize signal strength and minimize latency in dynamic environments. Exploring advanced cybersecurity measures will also be crucial to safeguard the integrity of transmitted data, particularly in high-stakes scenarios. Finally, a comprehensive evaluation of the system's performance in various disaster scenarios will be conducted, providing insights into the scalability and adaptability of UAV-based communication systems in real-world applications.

References

[1] Mingzhe Chen, Ursula Challita, Walid Saad, Changchuan Yin, and Mérouane Debbah. 2019. Artificial neural networks-based machine learning for wireless networks: A tutorial. *IEEE Communications Surveys & Tutorials* 21, 4 (2019), 3039–3071.

[2] Milan Erdelj, Enrico Natalizio, Kaushik R Chowdhury, and Ian F Akyildiz. 2017. Help from the sky: Leveraging UAVs for disaster management. *IEEE Pervasive Computing* 16, 1 (2017), 24–32.

[3] Margarita Gapeyenko, Vitaly Petrov, Dmitri Moltchanov, Sergey Andreev, Nageen Himayat, and Yevgeni Koucheryavy. 2018. Flexible and reliable UAV-assisted backhaul operation in 5G mmWave cellular networks. *IEEE Journal on Selected Areas in Communications* 36, 11 (2018), 2486–2496.

[4] Hailong Huang and Andrey V Savkin. 2018. A method for optimized deployment of unmanned aerial vehicles for maximum coverage and minimum interference in cellular networks. *IEEE Transactions on Industrial Informatics* 15, 5 (2018), 2638–2647.

[5] Qingqing Wu, Yong Zeng, and Rui Zhang. 2018. Joint trajectory and communication design for multi-UAV enabled wireless networks. *IEEE Transactions on Wireless Communications* 17, 3 (2018), 2109–2121.