Deep Learning-Driven Throughput Enhancement in Hybrid RF/VLC Systems for 5G and Beyond

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Abstract:

The rapid advancement of fifth-generation (5G) mobile communication systems has led to the increasing demand for innovative and efficient communication technologies. Hybrid systems combining light fidelity (LiFi) and wireless fidelity (WiFi) communication, commonly known as hybrid WiFi/LiFi systems, have emerged as promising candidates to fulfil this demand. These systems use the non-interfering spectra of both technologies to boost data rates and improve reliability, especially in dynamic environments with physical obstructions. However, optimizing resource allocation in these hybrid systems presents significant challenges due to the dynamic nature of the network and the non-concavity of the joint optimization problem involving bandwidth, user association, and power allocation.

This thesis proposes and evaluates advanced deep reinforcement learning (DRL) techniques to address the resource allocation problem in hybrid communication systems. First, we introduce a Deep Q-Network (DQN) based transfer learning algorithm that improves throughput in hybrid WiFi/LiFi systems by adapting to the dynamic network conditions and the entry of new mobile users. Simulation results demonstrate that this approach outperforms traditional optimization algorithms in terms of data rate maximization.

Next, we extend the work to dynamic hybrid radio frequency (RF) and LiFi networks, which combine the broad coverage of RF with the high data rates of LiFi. A model-free DRL approach is employed to solve the resource management problem under real-world conditions such as user mobility and signal blockages. This approach, which directly interacts with the environment, significantly enhances resource utilization and network performance, achieving a substantial increase in sum rate and optimal transmit power compared to conventional methods.

Finally, the thesis explores the integration of the susceptibility of visible light communication (VLC) to blockages, where its co-deployment with RF ensures uninterrupted connectivity in heterogeneous network environments. We introduce two on-policy DRL schemes—advantage actor-critic (A2C) and proximal policy optimization (PPO)—which optimize resource allocation and load balancing in large and dynamic hybrid RF/VLC systems. Simulation results show that the A2C and PPO schemes outperform existing DQN and deep deterministic policy gradient (DDPG) approaches, resulting in significant improvements in data rates and overall system performance.

The findings of this thesis contribute to the development of efficient hybrid communication systems for 5G and beyond, offering new insights into the application of DRL techniques for real-time resource optimization in dynamic and complex environments.

The thesis has been organized as follows:

Chapter 1: Introduction

This chapter introduces the motivation and background for hybrid communication systems, particularly the combination of LiFi/WiFi and RF/VLC technologies. It discusses the importance of efficient resource allocation and the challenges posed by dynamic network conditions, blockages, and user mobility. The chapter outlines the key objectives of the thesis, emphasizing the role of deep reinforcement learning (DRL) in addressing these challenges.

Chapter 2: Literature Review

A comprehensive review of existing research on hybrid communication systems is presented in this chapter. The review covers traditional optimization methods, recent developments in deep learning-based approaches, and the evolution of hybrid systems, including LiFi/WiFi and RF/VLC combinations. Gaps in the current literature are identified, highlighting the need for advanced, model-free DRL techniques to tackle resource allocation problems in dynamic and large-scale networks.

Chapter 3: DQN-Based Transfer Learning for Hybrid WiFi/LiFi Systems

This chapter presents a deep reinforcement learning-based approach using Deep Q-Networks (DQN) combined with transfer learning to optimize resource allocation in hybrid WiFi/LiFi systems. The chapter explores the challenges in dynamic environments where users frequently enter and exit the network, requiring adaptive optimization of bandwidth, power, and user association. The proposed DQN-based method addresses these challenges by leveraging transfer learning to quickly adapt to new users without retraining, improving overall network throughput. Simulations validate the algorithm’s efficiency, showing superior performance in dynamic conditions compared to existing optimization approaches.

Chapter 4: Deep Reinforcement Learning for Resource Allocation in Hybrid RF/LiFi Networks

This chapter focuses on a model-free deep reinforcement learning (DRL) approach for efficient resource allocation in hybrid RF/LiFi networks. The method does not rely on predefined models, learning instead from real-world interactions within the environment. It effectively handles challenges like blockages and user mobility by dynamically optimizing resource allocation. The chapter highlights how the DRL model significantly improves network performance, enhancing data rates and power efficiency over traditional techniques, as demonstrated through simulations.

Chapter 5: On-Policy DRL for Dynamic Resource Allocation and Load Balancing

This chapter investigates advanced on-policy deep reinforcement learning algorithms for resource allocation and load balancing in hybrid RF/VLC systems. Two schemes—advantage actor-critic (A2C) and proximal policy optimization (PPO)—are developed to handle the demands of dynamic, large-scale networks. The chapter explores how these algorithms optimize data rates and improve load balancing efficiency, offering substantial performance gains over existing solutions. Simulation results demonstrate the superiority of these methods in achieving higher data rates and better resource allocation compared to other reinforcement learning techniques.

Chapter 6: Summary and Conclusion

This chapter summarizes the contributions of the thesis, emphasizing the impact of DRL techniques on resource allocation and load balancing in hybrid communication systems. It discusses the key findings, the improvements over traditional methods, and potential future directions for research in this field.