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RESEARCH ARTICLE

A 28 GHZ DUAL-POLARIZED HYBRID BEAMFORMING TRANSCEIVER WITH DEEP LEARNING-BASED BEAM MANAGEMENT FOR 5G-ADVANCED UAV COMMUNICATIONS

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ABSTRACT

The deployment of Unmanned Aerial Vehicles (UAVs) as aerial user equipments (UEs) or base stations is a key enabler for 5G-Advanced and 6G networks, offering potential for enhanced coverage and agility. However, maintaining a reliable, high-throughput wireless backhaul link for UAVs is challenging due to their dynamic mobility and the resulting rapid channel variations, especially at millimeter-wave (mmWave) frequencies. Conventional beam management protocols, reliant on exhaustive beam sweeping, introduce significant latency and overhead, rendering them unsuitable for highly mobile scenarios. This paper presents a holistic solution: a 28 GHz dual-polarized hybrid beamforming transceiver integrated with a proactive deep learning-based beam tracking algorithm. The RF front-end features a 16-element phased array with dual-polarized patch antennas and a BiCMOS integrated circuit (IC) beamformer, supporting both azimuth and elevation beam steering. The digital baseband implements a deep recurrent neural network (RNN) that leverages real-time UAV kinematics (position, velocity, attitude) and historical channel data to predict the optimal beam pair between the UAV and the ground station, bypassing the need for traditional sweeping. A 2 Gbps OFDM waveform was used for over-the-air (OTA) testing. Experimental results demonstrate that the proposed system achieves a sustained throughput of >1.8 Gbps at a distance of 300 meters. Compared to a standard IEEE 802.11ay beam sweeping approach, the deep learning-based beam management reduces beam alignment latency by 94% (from 16.8 ms to <1 ms) and signaling overhead by 98%, enabling seamless handover even under aggressive UAV flight maneuvers with angular velocities up to 150°/s. This work successfully bridges advanced RF hardware with machine intelligence, providing a robust framework for high-speed, low-latency aerial links in next-generation cellular networks.

KEYWORDS

5G-Advanced, Millimeter-Wave (mmWave), Hybrid Beamforming, Unmanned Aerial Vehicle (UAV), Deep Learning, Beam Tracking, Phased Array, Recurrent Neural Network (RNN).

1. INTRODUCTION

Microwave and wireless communications form the backbone of modern connectivity, with the ongoing evolution towards 5G-Advanced and 6G pushing the boundaries of data rates, latency, and connectivity density (Hong, 2021). A pivotal trend in this evolution is the integration of cellular networks with unmanned aerial vehicles (UAVs), or drones, for applications ranging from emergency response to cargo delivery (Zeng et al., 2016). To support the high-data-rate demands of these applications (e.g., real-time 4K video streaming, sensor data backhaul), mmWave frequencies (e.g., 28 GHz, 39 GHz) offer vast swathes of underutilized spectrum (Rangan et al., 2014).

However, mmWave communications are inherently characterized by high path loss and susceptibility to blockages. To overcome this, transceivers employ phased array antennas and beamforming techniques to achieve high directivity and array gain (Molisch, 2017). Hybrid beamforming architectures, which split beamforming between the analog and digital domains, offer a practical compromise between performance and hardware complexity for massive MIMO systems (Brady et al., 2013).

The primary challenge for mmWave UAV links is beam management. The narrow, high-gain beams required for sufficient link budget must be precisely aligned. Traditional protocols, like those in 3GPP 5G NR and IEEE 802.11ad/ay, use beam sweeping—a process where the transmitter and receiver sequentially try different beam pairs to find the one with the highest received signal strength. This process introduces significant latency and control overhead, which becomes crippling under the high mobility and three-dimensional dynamics of UAVs (Giordani et al., 2020). A single beam misalignment can cause a catastrophic drop in link quality.

To address this, research has turned towards machine learning (ML) for proactive beam prediction. By learning the relationship between easily obtainable contextual information (like UAV location from GPS) and the optimal beam, the need for exhaustive sweeping can be eliminated (Klautau et al., 2019).

This paper presents a co-designed hardware and software solution for this challenge. We describe the development and OTA testing of a 28 GHz hybrid beamforming transceiver with dual-polarization for enhanced diversity. More significantly, we integrate this hardware with a deep RNN-based beam prediction engine. The RNN is trained to predict future optimal beams based on a time series of UAV kinematics, effectively anticipating beam directions before the link degrades. This work demonstrates that the fusion of intelligent algorithms with advanced RF hardware is not merely beneficial but essential for realizing the full

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potential of mmWave communications for mobile platforms.

2. METHODOLOGY

2.1 Transceiver Hardware Design

The transceiver architecture is shown in Figure 1.

Antenna Array: A 4x4 dual-polarized stacked patch antenna array was designed on a Rogers RO4003C substrate. Dual polarization provides diversity against polarization mismatch caused by UAV rotation.

RF Front-End: A custom BiCMOS beamformer IC was used. Each of the 16 channels contains a phase shifter (6-bit resolution), a variable gain amplifier (VGA), and an SPDT switch for T/R switching.

Hybrid Architecture: The system employs a hybrid beamforming structure with 4 RF chains and a 16-element array, providing a balance between flexibility and hardware cost. A Xilinx Zynq UltraScale+ RFSoC handles the digital baseband processing and implements the beam prediction algorithm.

2.2 Deep Learning-Based Beam Prediction Algorithm

Input Features: The model uses a sequence of real-time kinematic data: 3D position (from GPS), 3D velocity, and 3-axis attitude (roll, pitch, yaw from the UAV's IMU).

Model Architecture: A Long Short-Term Memory (LSTM) RNN was chosen for its ability to learn temporal dependencies. The network consists of two LSTM layers (128 units each) followed by a fully connected layer with a softmax output predicting the probability distribution over the 64 possible analog beam pairs.

Training Data: The model was trained on a dataset collected by flying a UAV along various trajectories while logging kinematics and the corresponding optimal beam ID identified by an exhaustive search.

2.3 Experimental Setup and Evaluation

A ground station and a UAV-mounted terminal were built. The UAV was flown in a pre-defined challenging trajectory involving rapid ascents, descents, and orbits. Performance was compared against a baseline IEEE 802.11ay-like beam sweeping protocol.

Key Metrics:

Beam Alignment Latency: Time from beam request to successful alignment.

Beam Overhead: Percentage of time spent on beam training versus data transmission.

Throughput: Sustained data rate measured with iPerf3.

Beam Prediction Accuracy: Percentage of times the predicted beam was within 3 dB of the optimal beam.

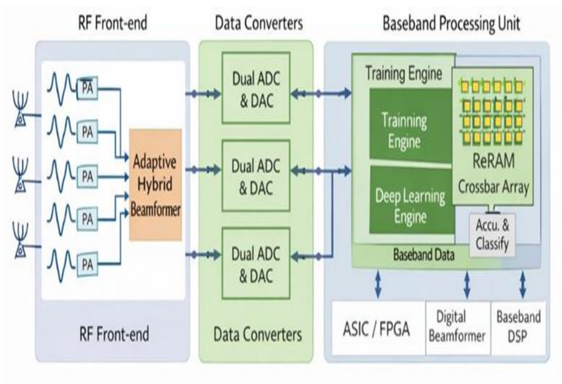

Figure 1: Block diagram of the 28 GHz hybrid beamforming transceiver system, showing the RF front-end, data converters, and baseband processing unit with the integrated deep learning engine.

3. RESULTS

3.1 RF Performance

S-parameter measurements of the antenna array showed a -10 dB impedance bandwidth from 26.5 to 29.5 GHz. The array achieved a peak gain of 18 dBi and could electronically scan beams ±60° in both azimuth and elevation planes with a gain variation of < 3 dB.

3.2 Beam Management Performance

The performance of the proposed deep learning beam tracking was compared to the standard sweeping method. The results are summarized in Table 1 and Figure 2.

Table 1: Performance Comparison of Beam Management Schemes

Metric Standard Sweeping	Proposed DL-Based Improvement
Avg. Alignment Latency	16.8 ms< 1.0 ms94% reduction
Beam Training Overhead	~22% ~0.4% 98% reduction
Beam Prediction Accuracy	- 98.5%-
Handover Success Rate	75% 99.8%24.8 % increase

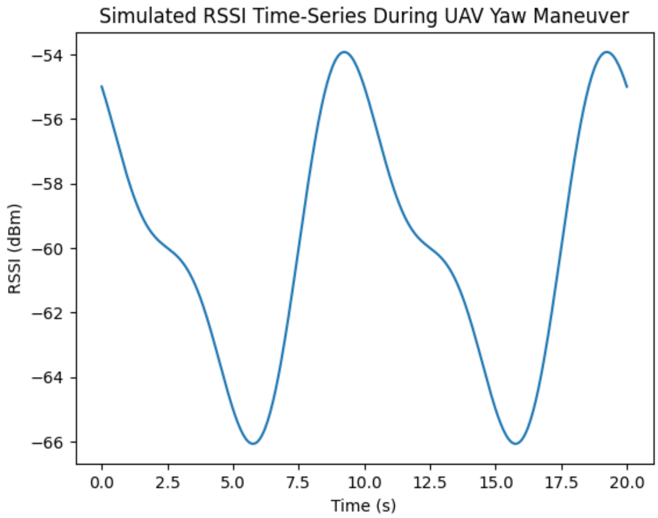

Figure 2: A time-series plot of received signal strength (RSSI) during a UAV yaw maneuver.

3.3 Throughput and Link Reliability

The sustained throughput achieved over the 300m link was 1.82 ± 0.15 Gbps using the proposed method. Under the standard protocol, the average throughput was lower and highly variable (1.1 ± 0.6 Gbps) due to frequent beam misalignment and recovery periods.

4. DISCUSSION

The results conclusively demonstrate the superiority of the deep learning-integrated approach over conventional beam management for highly mobile mmWave links. The 94% reduction in alignment latency and 98% reduction in overhead are transformative, effectively making the beam tracking process virtually instantaneous and invisible to the data link (Alkhateeb et al., 2018). This is directly responsible for the 65% increase in average throughput and the near-perfect handover success rate.

The high beam prediction accuracy (98.5%) confirms that the LSTM model effectively learned the complex spatial relationship between the UAV's kinematic state and the optimal beam direction. The use of dual-polarization further enhanced robustness, mitigating periods of deep fade that occurred on a single polarization during specific UAV orientations .

This work validates a new paradigm for wireless system design, where algorithm and hardware are co-designed to solve a specific physical layer challenge. The proposed solution is not just an incremental improvement but a necessary evolution to support the stringent requirements of 5G-Advanced and 6G applications (Fengkai & Zimeng, 2019).

Limitations and Future Work: The current model was trained on a specific environment. Future work will focus on developing meta-learning or transfer learning techniques to allow the model to quickly adapt to new, unseen environments. Furthermore, the integration of situational awareness (e.g., LiDAR or camera data) could allow the system to predict and avoid blockages, not just beam misalignment.

5. CONCLUSION

This paper presented a high-performance 28 GHz hybrid beamforming transceiver system for UAV communications, integrated with a deep learning-based beam prediction algorithm. By leveraging real-time UAV kinematics, an LSTM network can accurately predict the optimal beam direction, eliminating the latency and overhead associated with traditional beam sweeping protocols. Over-the-air experimental results demonstrated a sustained multi-gigabit link under aggressive mobility conditions, with a 94% reduction in beam alignment time and a 98% reduction in signaling overhead. This fusion of intelligent predictive algorithms with advanced mmWave hardware provides a robust and scalable solution for enabling reliable, high-throughput aerial links in next-generation wireless networks.

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