3D RF Coverage Mapping Using Aerial Drone Data

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Project Objective and Background

Traditional methods of Radio Frequency (RF) data collection and coverage mapping are resource-intensive and lack 3D mapping capabilities. 3D RF data collection using a drone enables optimization of home internet device placement for T-Mobile's 5G network.

Project Objective and Requirements:

- Use 3D drone positioning to gather RF data
- Create a 3D visualization of RF and performance metrics
- Develop statistics and ML models to identify optimal sites for outdoor wireless home internet device placement

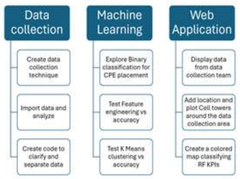


Figure 1: Sub team Breakdown

Developing a Logging Strategy

- Manual data collection was used before the arrival of the drone to develop collection methods and familiarize the group with the collection software
- Perimeter test was developed to test the RF antenna at various places the drone data could be taken
- Preliminary tests were expanded into 3D using QGroundControl, a drone flight planning software
- **Final approach:** Three 2D flights stacked at different altitudes. Drone flies in a snake-pattern survey.

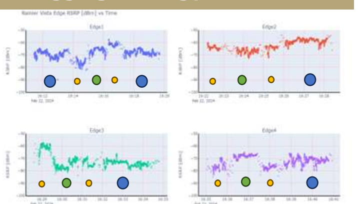


Figure 2: Rainer Vista KPIs

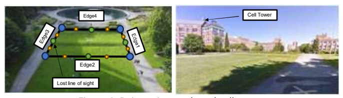
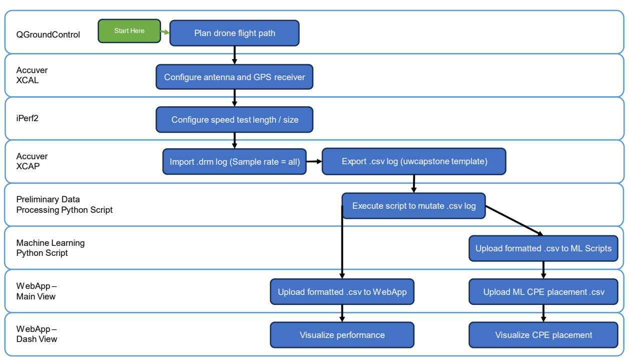


Figure 3: Rainer vista path and cell tower

Perimeter Test: Student walks around the perimeter of the test area running speed tests of alternating durations to find the minimum speed test duration and network ramp-up time.

User Flowchart



Data Preprocessing

- Conduct preliminary data shaping/analysis including:
  - Forward/back fill missing data
  - Correct throughput for traffic
  - Combine & label 3 flights at different altitudes
  - Drop takeoff/landing data
- ML preprocessing:
  - Convert non-numeric data to Boolean values for Neural Network
  - Distance feature calculated in meters between 5G tower and datapoints
  - Assigned a score to each location depending on throughput, RSRP, RSRQ & SINR metrics

Raw data before processing

Raw data after processing

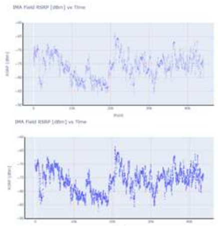


Figure 4: RSRP pre vs post processing

Model Training & Methods (ML)

Clustering

- Used Gaussian Mixture Modeling to cluster the highest score grouping of points to find best CPE placement [1]
- Tested optimal number of clusters using BIC scoring for GMMs

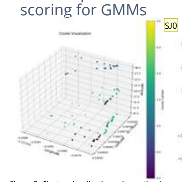


Figure 5: Cluster visualization using optimal number of clusters on highest score grouping

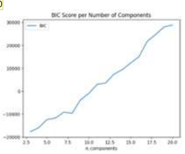


Figure 6: BIC scoring for GMMs

Deep Learning

- Trained model to predict corrected throughput using Neural Network
- Neural network built with one hidden layer, 43 input and 1 output
- Achieved a prediction accuracy of 90% within 10 Mbps (True vs predicted)

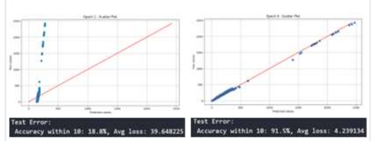


Figure 7: Epoch 1 vs Epoch 9 accuracy and loss using Mean Absolute Error loss function

Machine Learning Results

Clustering

At the optimal CPE location, three out of four key metrics surpassed the threshold for excellent, while one was at the border between excellent and good

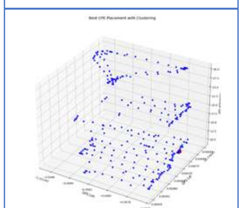


Figure 8: Optimal CPE placement (red point) among dataset

Deep Learning

Using neural networks, the corrected throughput is predicted based on other features and RF KPIs. This model is saved and can be used on other data sets. CPE placement is picked through maximum predicted throughput

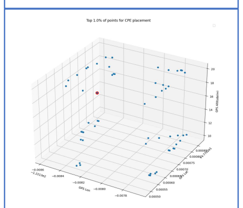


Figure 9: Optimal CPE placement (red point) top 1% of dataset

ML optimal CPE placement KPIs		
	Clustering	Deep Learning
Score	11	9
Throughput	361.8 Mbps	433.35 Mbps
RSRP	-79.2 dBm	-81.55 dBm
RSRQ	-10.5 dB	-10.44 dB
SINR	20.6 dB	19.42 dB
Runtime	10.6 seconds	10.3 minutes (train) 2 minutes (eval)
Recommendation	Efficiency	Larger Dataset

Recommendations:
For quick CPE placement, clustering would be the best as shown by the 10.6 seconds runtime. Although, deep learning would be our recommendation for larger datasets because after training the prediction model, multiple datasets can be evaluated on the saved neural network.

Web Application Methods

Interactive map: An intuitive interface using HTML by integrating Mapbox GL JS library to handle the display of 3D buildings, data points, and various data layers on the map. [2]

- 3D Buildings Layer: Utilizes Mapbox's 3D building layer to display realistic structures.
- Points Layer: Displays points on the map representing CPE placement data obtained from CSV files, it visually depicts the throughput strength through varying colors.
- Coverage Circle Layer: Represents the coverage area based on the number of data points in a region.

Scatter 3D Plot Module: The scatter plots allow users to visualize the distribution of all data points by Plotly, PapaParse and Dash libraries. [3]

- Dash: Provides the necessary layout and callbacks for the scatter plots
- Plotly: Dynamically generates 3D scatter plots based on the user's selection from a dropdown menu
- PapaParse: Converts raw data into a GeoJSON format suitable for map rendering

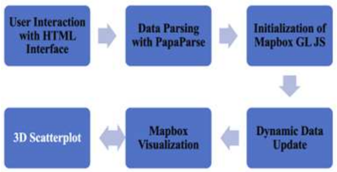


Figure 10: Webapp Flowchart

Web Application Visualizations

The interact web visualization provides a dynamic exploration of network performance metrics, optimal CPE placement, and insights into areas with the best CPE data.

- The clustering feature allows users to identify clusters of data points representing areas with similar network characteristics
- The web visualization highlights area with the best CPE placement based on corrected throughput value
- Users can select specific network performance metrics (e.g., RSRP, RSRQ, SINR) and visualize their spatial distribution

Figure 11: Cluster Visualization & the best CPE placement

Figure 12: 3D Scatter Plot

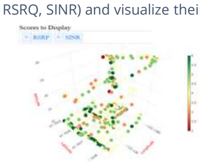


Figure 13: Score Distribution

Conclusion

The project enabled the student team to engage in the design and engineering process, transitioning from manual 2D data collection to utilizing QGroundControl for 3D flight data acquisition. They then processed this data with a script for integration into both machine learning models and a web application. The web app showcased both the ML results and processed data, providing a comprehensive overview of their efforts and valuable hands-on experience.

Future Work and References

Future Work:

- Web application can be expanded to have a larger variety of visualizations
- ML/Deep learning can be optimized for new 3-D datasets using trained models
- Integrate predictions and/or scoring for RSRP, RSRQ & SINR for deep learning method

References
[1] U. Masood, H. Farooq and A. Imran, "A Machine Learning Based 3D Propagation Model for Intelligent Future Cellular Networks," 2019 IEEE Global Communications Conference (GLOBECOM), Waikoloa, HI, USA, 2019, pp. 1-6
[2] "Mapbox docs," Mapbox, https://docs.mapbox.com/. [3] "Dash documentation & user guide," Plotly, https://dash.plotly.com/.

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