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Source: *SSN College of Engineering, Chennai*

Title: Dynamic Beamforming Optimization Using Genetic Algorithm for Mobile Devices, Fleets, and Drones in Multi-Antenna Systems

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Abstract: This project presents a solution for dynamic beamforming in multi-antenna systems using a genetic algorithm, applicable not only to mobile devices but also to fleets and drones that require continuous monitoring. Conventional static or adaptive beamforming mechanisms become inefficient when devices, fleets, or drones are in motion. This proposal uses historical antenna weight values and signal strength data to predict optimal weight adjustments in real-time. A genetic algorithm explores a search space of potential weights, applying crossover and mutation techniques to maintain strong connectivity despite the uncertain movement of devices. This approach enhances wireless network performance in highly dynamic and complex environments, such as transportation fleets, drone operations, and mobile communication systems.

Use case introduction:

In modern wireless systems, maintaining optimal beamforming is challenging when devices, vehicles, or aerial systems (such as drones) are moving. For example, in fleets or drone monitoring operations, real-time beamforming is crucial for maintaining uninterrupted connectivity. The proposed system dynamically adjusts antenna weight values to ensure consistent and strong signal strength, even as the monitored entities are in motion. By using a genetic algorithm, the system adapts to changes without relying on exact positional data, making it suitable for a variety of real-time, dynamic applications.

Phase 1:
A device, fleet vehicle, or drone connects to the multi-antenna system. Initial antenna weight values are assigned, and signal strength is measured.

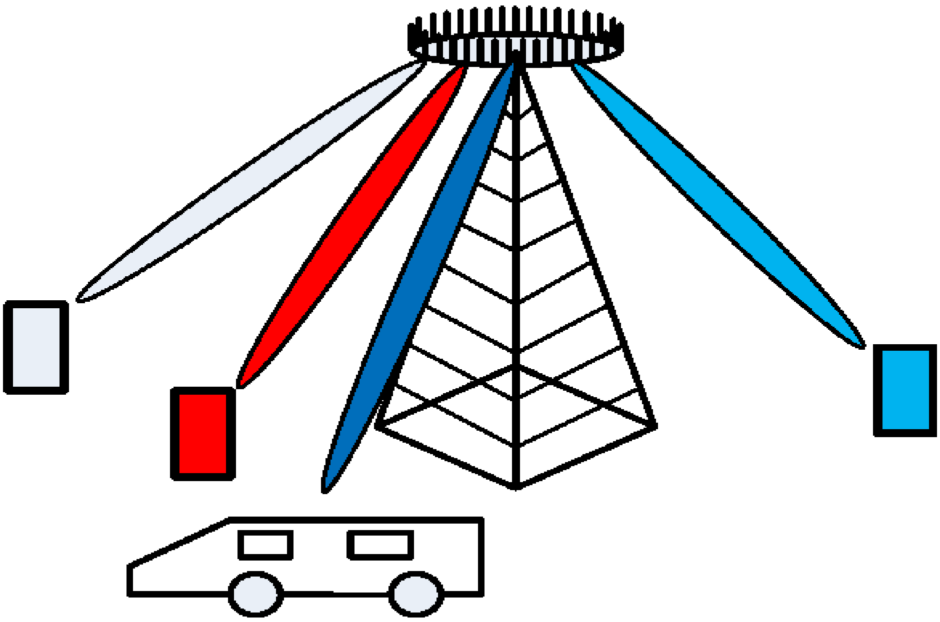
Phase 2:
The connected entity (device, fleet, or drone) begins to move. The system detects a change in signal strength, indicating the need for dynamic weight adjustment.

Phase 3:
The genetic algorithm is triggered. It initializes a population of weight values near the previous set, and signal strength is used to evaluate the fitness of each individual.

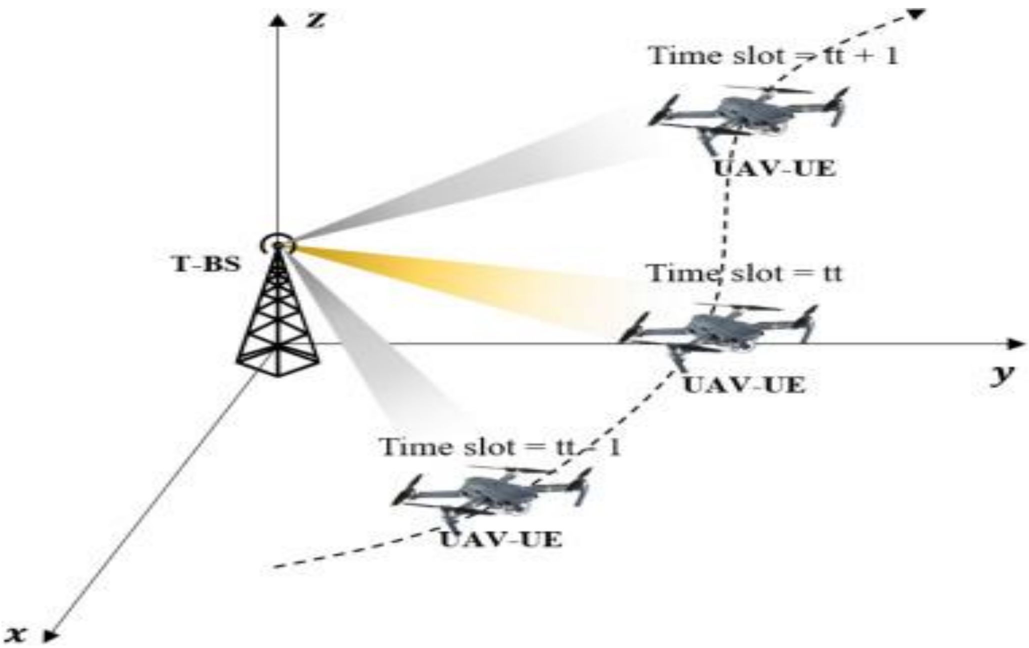
Phase 4:
The algorithm applies mutation and crossover to iteratively search for better weight values, continuously optimizing beamforming as the entity moves.

Phase 5:
Optimal weight values are found, signal strength is maximized, and the system maintains connectivity. Historical weight values are stored for future predictions.

Phase 6:
If the entity moves again, the system uses the learned weight values to predict the next optimal beamforming configuration, repeating the process as needed.



Dynamic Beam forming for Moving Vehicles



Dynamic Beam forming for Drones

Use Case Requirements:

- **Problem**: Current static beamforming methods struggle to maintain optimal connectivity in environments with moving devices, fleets, or drones.
- **Proposed Solution**: Use a genetic algorithm to dynamically adjust antenna weights based on historical weight values and signal strength data.
- **ML Concept**: Apply a genetic algorithm to optimize weight values in real time, ensuring connectivity for moving devices, fleets, and drones.

Pipeline design (Genetic Algorithm Design)

- **Initial Step**: When movement is detected (in devices, fleets, or drones), initialize a population of antenna weight values near the previous configuration.
- **Fitness Evaluation**: Signal strength serves as the fitness function to rank the effectiveness of each weight configuration.
- **Genetic Operations**: Crossover and Mutation are performed iteratively to explore better configurations.
- **Convergence**: The algorithm quickly identifies the optimal weight values to maintain signal strength.

Relation to Standards

According to ITU Y.3601 – Autonomous Networks

An intelligent solution based on automatically optimized beam forming - providing seamless connectivity services for fast-moving mobile devices. Reinforcement modeling and inference, facilities parameters control policies decision, facilities adjustment actions implementation, result evaluation, and continuous optimization.

Optimal adjustment of antenna beamforming parameters with AI-enabled multi-dimensional analysis and prediction

The proposed solution aligns with ITU Y.3601 in several aspects:

- Dynamic Beamforming: The recommendation emphasizes the importance of dynamic beamforming in wireless access systems.
- Optimization Methods: ITU Y.3601 mentions optimization techniques, including genetic algorithms, for beamforming.
- Multi-Antenna Systems: The recommendation addresses multi-antenna systems, which are crucial for dynamic beamforming.
- Mobile Devices, Fleets, and Drones: ITU Y.3601 considers various wireless devices, including mobile devices, fleets, and drones.

Relation To SDG's

SDG 9: Industry, Innovation, and Infrastructure

- Develop efficient and reliable communication infrastructure (Target 9.1).

- Enhance technological capabilities for industrial diversification (Target 9.4).
- Foster innovation and entrepreneurship (Target 9.5).

SDG 11: Sustainable Cities and Communities

- Develop and implement sustainable transportation systems (Target 11.2).
- Enhance public transportation efficiency and accessibility (Target 11.2).
- Reduce the environmental impact of urbanization (Target 11.6).

SDG 12: Responsible Consumption and Production

- Implement efficient resource utilization and management (Target 12.2).
- Reduce electronic waste through optimized device performance (Target 12.5).

SDG 13: Climate Action

- Mitigate climate change through reduced energy consumption (Target 13.2).
- Promote sustainable technologies and practices (Target 13.3)

The proposed technology contributes to these SDGs by:

1. Enhancing communication efficiency and reliability.
2. Reducing energy consumption and environmental impact.
3. Promoting sustainable transportation and infrastructure.
4. Supporting innovation and entrepreneurship.
5. Improving public services and accessibility.

Some potential indicators to measure the impact of this technology on SDGs:

1. Network energy efficiency (Gbps/Watt).
2. Carbon footprint reduction (tons CO2e).
3. Increased connectivity and accessibility (%).
4. Improved transportation efficiency (reduced travel time, increased safety).
5. Number of jobs created and economic benefits generated

Code submission

Github link: https://github.com/Srikanth-Drklrd/MIMO_Genetic_Algorithm.git

Contains:

- Input Document
- Code Implementations in Jupyter notebook (.ipynb)
- Result in Jupyter notebook (.ipynb)

References

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2. Hu, Z., & Hsu, H. T. (2019). Efficient Adaptive Subarrays in Millimeter-Wave MIMO Systems With Hybrid RF/Baseband Precoding Combining Design. IEEE Transactions on Vehicular Technology, 68(2), 1713-1726, doi: 10.1109/TVT.2018.2887367.

3. IEEE Standard 802.11ad-2012, “Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications—Amendment 3: Enhancements for Very High Throughput in the 60 GHz Band.”
4. Qu, C., Peng, X., & Zeng, Q. (2024). Learning search algorithm: framework and comprehensive performance for solving optimization problems. *Artificial Intelligence Review*, *57*(6), 139.

Appendix A:

1. Concept Explanation

This appendix outlines the core concepts and methods used for dynamic beamforming in tracking moving devices, focusing on hybrid beamforming, genetic algorithms, and real-time feedback mechanisms.

2. Hybrid Beamforming

Hybrid beamforming combines analog and digital beamforming to achieve high-performance beam steering while reducing hardware complexity. In the context of moving devices, hybrid beamforming dynamically adjusts subarrays and RF chains to maintain connectivity, balancing between power efficiency and high throughput. The system adapts to changes in device positions by leveraging both phase shifting (analog) and digital signal processing.

3. Genetic Algorithm for Beamforming Optimization

A genetic algorithm (GA) is employed to dynamically optimize the antenna weights in response to device movement. The GA adapts by initializing a population of weight values based on prior configurations (historical signal strength), and through iterative selection, crossover, and mutation, finds the optimal beamforming pattern. This enables real-time adaptability without requiring exact device location data.

4. Beam Codebook and Adaptive Search

The system uses a pre-defined **beam codebook**, which simplifies the search space for beamforming directions. The genetic algorithm operates within this codebook to rapidly find the most efficient beam patterns. The use of adaptive search techniques helps optimize connectivity as the device moves.

5. Beam Tracking

Real-time feedback through beam tracking algorithms (e.g., Kalman Filters) ensures that the system continuously adjusts the beam direction as the device moves. This is particularly important in mmWave communications, where beam directionality is crucial to overcoming path loss and maintaining high signal strength.

Appendix B:

Genetic Algorithm Overview:

In this section, we explain the Genetic Algorithm (GA) implemented in the Python notebook for dynamic beamforming in multi-antenna systems.

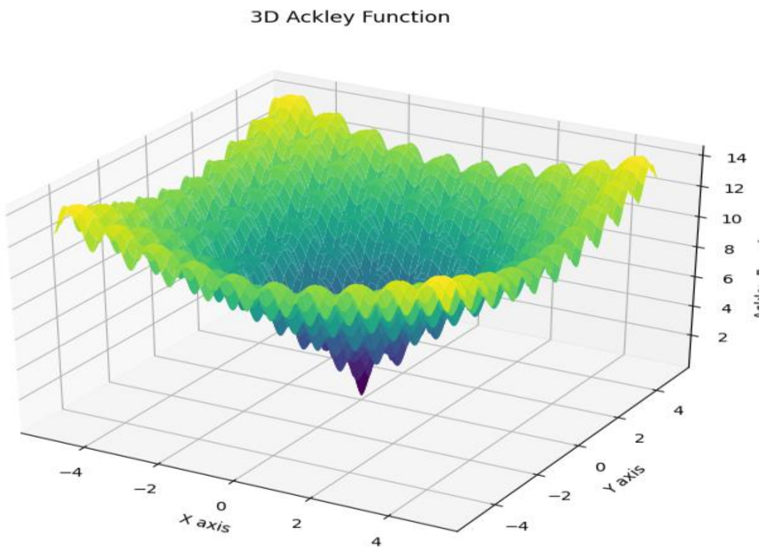
1. Initialization:

The GA starts by initializing a population of potential solutions (antenna weight values). These solutions are initialized near the previous optimal weight configuration to ensure the search starts from a reasonable point in the solution space. If the last optimal weight configuration is unavailable, then the search begins at a random point.

2. Fitness Function:

The fitness of each solution is evaluated based on the signal strength obtained from the antenna configuration. Higher signal strength results in higher fitness scores. This metric ensures that the algorithm is always optimizing toward the best connectivity for mobile devices, fleets, and drones.

Here we use, the dynamic time-varying Ackley function to effectively model the challenges faced by a drone's antenna system as it navigates through different spatial and temporal conditions. The dynamic Ackley function is often used in optimization problems due to its complex landscape, which includes multiple local minima and a single global minimum. When considering its movement in the x, y, and z directions over time, you can think of it as a three-dimensional surface that changes dynamically, creating a rich landscape that can simulate various conditions.



Reasons for Using Ackley function as fitness function and model for drone antenna beamforming

1. **Global Minima and Antenna Orientation**: The global minima of the Ackley function can be likened to optimal antenna orientations. Just as the Ackley function seeks to minimize energy, an optimal polarization map indicates the best configuration for signal reception or transmission.
2. **Movement in Space**: As the Ackley function dynamically changes with respect to time, it can represent a drone moving through various environmental conditions. The changing surface might reflect varying signal strengths, obstacles, or atmospheric effects affecting the antenna's performance.

3. **Complex Landscape**: Both the Ackley function and the antenna map involve navigating complex landscapes. The Ackley function's rugged terrain represents challenges like interference or multipath propagation that a drone might encounter as it moves.
4. **Optimization**: The goal in both scenarios is optimization. For the Ackley function, it's finding the minimum, while for the drone, it's about finding the best antenna configuration for given conditions, possibly adapting in real-time as the environment changes.

3. Selection:

Selection involves choosing the fittest individuals from the current population for reproduction. In our implementation, individuals with better fitness (stronger signal strength) have a higher probability of being selected.

4. Crossover (Recombination):

Crossover is applied to the selected individuals to produce the next generation. In this step, portions of the antenna weight values from two parent solutions are combined to create a new solution. This encourages the exploration of new configurations while regaining the properties of the parent.

5. Mutation:

Mutation introduces small random changes to individual solutions. This step is crucial for maintaining diversity within the population and avoiding premature convergence on suboptimal solutions. Since vehicle motion can be abrupt and random, introducing some amount of randomness in the search process could prove to be beneficial.

6. Adaptive Learning:

As the GA operates, it learns from the historical weight values and signals strengths, enabling it to predict the next optimal weight configurations when the device, fleet, or drone moves again.

7. Error function:

The Euclidean distance between the estimated genetic algorithm and the actual point of maximum signal strength is used as an error function.