Evolving Antennas For Directional Radio Sensitivity

Dylan Wells(1), Julie Rolla(2), Bryan Reynolds(3), and Amy Connolly(1)

(1) Ohio State University, Columbus, Ohio 43210, USA, wells.1629@osu.edu
(2) Jet Propulsion Laboratory, NASA, Pasadena, CA 91109
(3) Remcom, State College, PA 16801

***Abstract*—This work presents a genetic algorithm that evolved antennas with specified directional sensitivity. The algorithm constructs antennas by combining geometric shapes like building blocks, where the fitness is determined by the directionality of the antenna's radiation pattern. This paper demonstrates that the algorithm is capable of evolving antennas towards maximizing gain in desirable directions while simultaneously minimizing gain in undesirable directions for single-frequency (300 MHz) and broadband (200 MHz to 800 MHz) applications.**

I. Introduction

This paper describes a genetic algorithm (GA) that designs antenna geometries towards maximizing sensitivity in specified directions. The antennas are constructed without any knowledge of traditional antenna designs. Similar techniques were used in the NASA Space Technology 5 (ST5) mission. Their GA created a wire antenna for satellite communications that outperformed human-designed counterparts [1]. Recently, GAs been utilized by the Genetically Evolved NEutrino Telescopes for Improved Sensitivity (GENETIS) project to optimize antenna designs towards greater sensitivity to neutrinos, showing a 22 percent improvement over human-engineered designs [2]. The efforts presented build on previous work by removing the need for a predetermined antenna geometry and adding multiple primitive shapes. The algorithm combines these primitive shapes to design unique antennas. We then evolve the antennas towards a mathematical fitness function based on outputs from electromagnetic simulation software XFdtd by Remcom [3].

II. Genetic Algorithm

A GA is an optimization technique that borrows concepts from biological evolution [4]. It begins by initializing the genes for a random population of solutions, then assigning a fitness score to each individual. Fitness is the measure of how well each individual performs at the objective. Individuals that are more fit are more likely to become parents and pass their on genes to the next generation. Through repeating this process in a loop, evolutionary pressure guides the optimization towards better solutions. An illustration of the process is provided in Fig. 1.

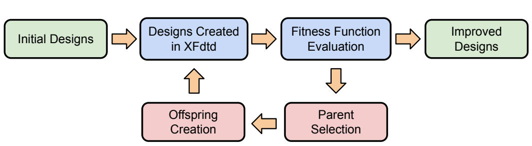


Fig. 1. Graphical illustration of the genetic algorithm's looping process.

A. Building an Antenna

The algorithm constructs each antenna from combining a set of primitive shapes (cuboids, spheres, cones, cylinders), creating a more complex overall structure. Each shape in the individual is described by its dimensions, rotation, and placement on the previous shape. For this exploration we have added additional conditions for the geometries. We define the origin as the voltage feed and ground points of the structure - building the two sides of the antenna off of the feeds. Each shape is restricted to only have one connecting shape per surface. To prevent poor performance due to unintended shorting, we have added an additional collision detection constraint to prevent the two distinct sides of the antenna from touching. An additional constraint ensures antennas have between 2and 6 primitive shapes. An example individual without the feed constraint is illustrated in Fig. 2.

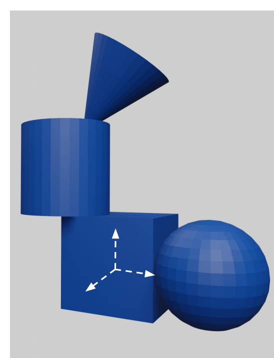


Fig. 2. Example individual geometry made from four primitive shapes. In this case the cuboid is the source shape, with the sphere and cylinder being placed on the cuboid. The cone is placed on the cylinder

B. Simulation in XFdtd

After generating the designs for each antenna, they are then modeled and simulated in XFdtd to retrieve a radiation pattern. This is done by converting the indivdual's geometry into an XFdtd model. We use hollow shapes made out of perfect electrically conducting material. We sample the antenna gain at steps of 5 degrees across both azimuth and elevation.

III. Fitness Function

The fitness function allows for user-specified regions in which to maximize and minimize the gain separately. The formula for total fitness F_{total} is given by

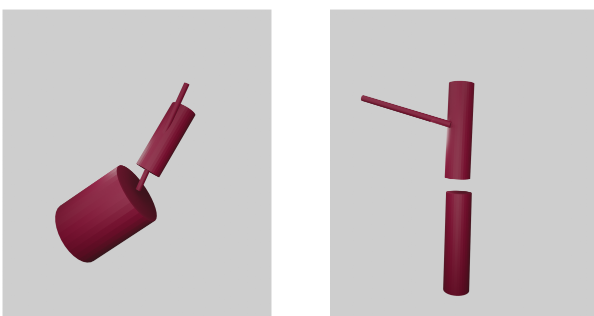
$$F_{total} = A\left[\tanh\left(\bar{G}(\theta_{max}, \phi_{max})\right)\right] + B\left[\bar{G}(\theta_{min}, \phi_{min}) + 1\right]^{-1} \quad (1)$$

Where $\bar{G}(\theta, \phi)$ is the average gain over all points in the given region, and A and B are the weights for the maximizing and minimizing components respectively. For this work, both regions are weighted equally, $A = B = 0.5$. The areas of minimization were between $0°$ to $45°$ and $135°$ to $180°$ in zenith. The area of maximization was between $45°$ and $135°$ in zenith. The fitness score for broadband environments is the average of F_{total} for all frequency steps.

IV. Results

A. Single Frequency Evolution

Fig. 3 highlights the change in design throughout the evolution. The individual shown from generation 142 first appeared as a standard dipole without the offshooting cylinder. The cylinder increased the directionality of the antenna's radiation pattern, performing better than the dipole counterpart. This shows the ability for the algorithm to create unique solutions.



Generation 0 ($F_{total} = 0.718$) **Generation 142** ($F_{total} = 0.881$)

Fig. 3. The geometries of the best individuals from generation 0 and generation 142

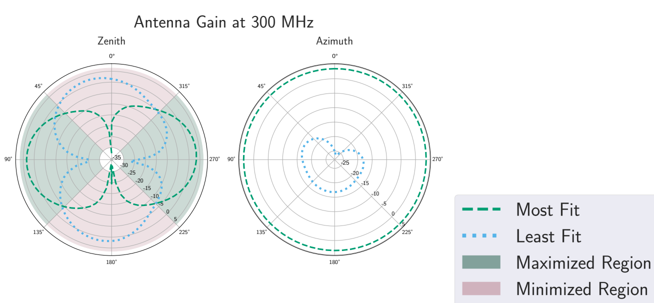
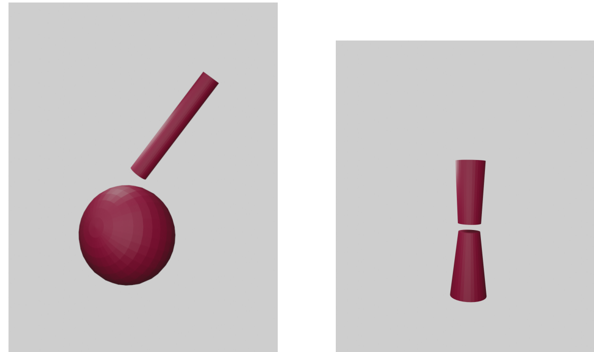


Fig. 4. Zenith and azimuthal slices of the best overall individual's gain pattern from generation 142.

B. Broadband Evolution

Fig. 5 and Fig. 6 show the results from the broadband evolution. As expected with a wider band of frequencies, the algorithm arrived at a thicker biconical antenna design.



Generation 0 ($F_{total} = 0.708$) **Generation 229** ($F_{total} = 0.821$)

Fig. 5. The geometries of the best individuals from generation 0 and generation 142

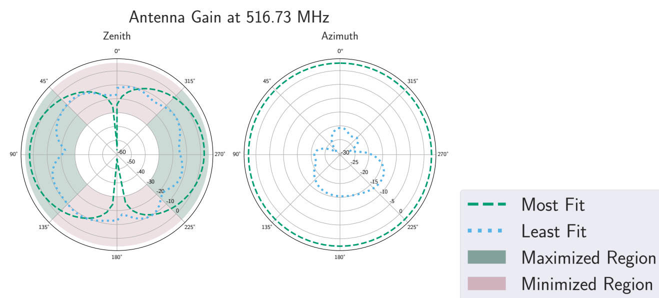


Fig. 6. Slices in zenith and azimuth of the best overall individual's gain pattern from generation 119

V. Conclusions

This work presents results of a GA capable of designing antennas sensitive in user-defined directions. Evolutionary runs in single-frequency (300 MHz) and broadband (200 MHz to 800 MHz) environments are presented. Future work will expand the algorithm to include different measures of fitness and expand the types of antennas it's capable of constructing.

Acknowledgement

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