A Comparison of Antenna Placement Algorithms

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Motivation

- Antenna placement study is generally ignored
- Placing new antennas requires a long, manual effort to complete an antenna placement study, if at all
- With multiple antennas systems offer interference, and thereby reduce each antenna's efficiency
- Parasitic effects due to fixed or mobile plaform
- Frequency bands change over time requiring new antennas, and therefore need to find new placements

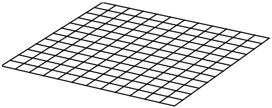
Outline of this talk

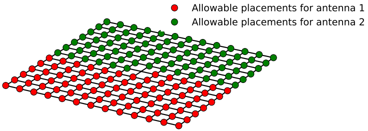
- Part 1: Introduction to the antenna placement problem
- Part 2: Description of stochastic algorithms, their properties and operators
- Part 3: Evaluation of test cases

Part 1: Introduction to the antenna placement problem

Antenna Placement Problem

Given, platform + allowable placements of antennas





Antenna Placement Problem

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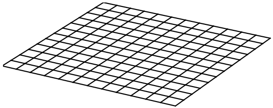
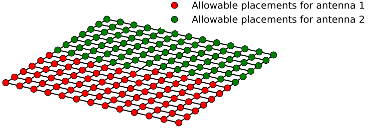
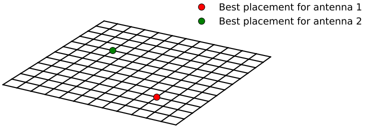




Problem: Find best antenna placements to maximize gain and minimize coupling



Antenna Placement Problem

Given:

- platform P with its surface gridded such that end points represent possible antenna placements
- set of n antennas $A = A_1, A_2, \ldots, A_n$ such that $n > 1$
- for each A_i, L_i denote the set of allowable placements $\in \mathbb{R}^3$ such that $\mid L_i \mid = m_i$ and $\forall i, m_i > 1$

$$L_i = \{(x_1, y_1, z_1) \ldots (x_{m_i}, y_{m_i}, z_{m_i})\}$$

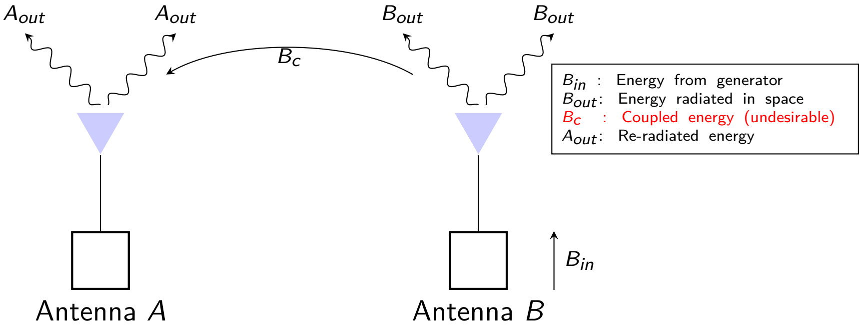
Problem: Find a set of n optimal antenna placements on P to maximize gain and minimize coupling.

Size of search space $= \mathbf{m^n}$, if $m_i = m, \forall i \in [1, n]$

Question: How is a good antenna placement quantified in the context of platform and other antennas?

Mutual Coupling

When two antennas are in proximity, and one is transmitting, the second will receive some of the transmitted energy.



Minimize Mutual Coupling

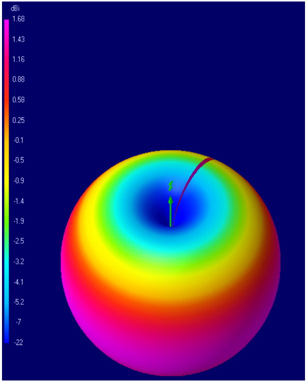
$$F_{MC} = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} CP(A_i, A_j), \qquad (1)$$

where

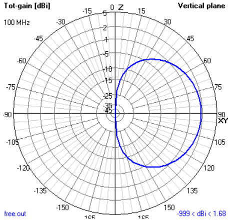
- $CP(\cdot,\cdot) \in \mathbb{R}$ is the coupling between two antennas, and computed using a simulator
- There will be $\binom{n}{2}$ coupling terms

Example: If $n = 3$, then $F_{MC} = CP(A_1, A_2) + CP(A_1, A_3) + CP(A_2, A_3)$

Free Space Radiation Pattern



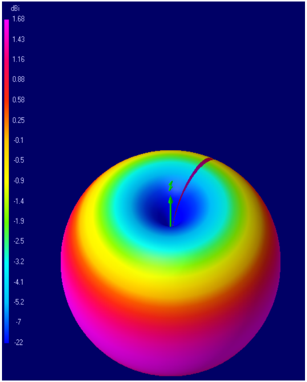
Free-space patten without platform or other antennas



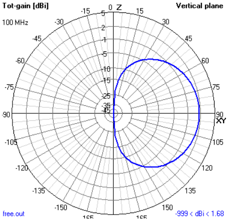
2D view of the free-space gain pattern

This is ideal pattern since there is no interference

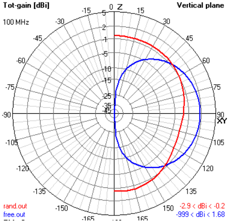
Radiation Pattern



Ideal gain pattern since there is no intereference



2D view of the free-space gain pattern



In-situ gain pattern for random antenna placements different from free-space gain pattern

Minimize Difference in Radiation Pattern

$$F_{RP} = \sum_{i=1}^{n} \sum_{\theta=0}^{\frac{180°}{S}} \sum_{\phi=0}^{\frac{360°}{S}} \left(FSG_i(S\theta, S\phi) - ISG_i(S\theta, S\phi)\right)^2, \quad (2)$$

where

- S is the step size
- θ, ϕ spherical coordinates in degrees
- $FSG(\cdot,\cdot) \in \mathbb{R}$ is the free-space gain pattern computed by the simulator
- $ISG(\cdot,\cdot) \in \mathbb{R}$ is the in-situ gain pattern computed by the simulator

Fitness Evaluation

Find a placement such that F is minimal:

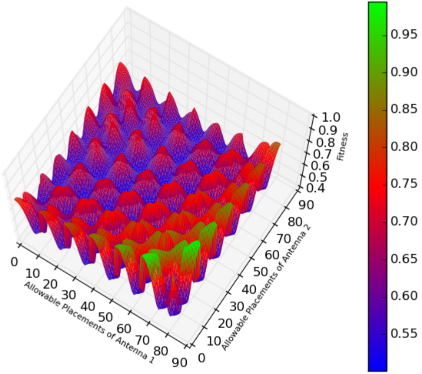
$$F = \alpha F_{MC} + \beta F_{RP}, \tag{3}$$

where α, β are adjustable weights for each of the objectives

Part 2: Stochastic Algorithms

Question: Why use stochastic algorithms?

Multi-Modal Search Space



Search space for one of the test cases evaluated. There are multiple local minimas which makes convergence difficult. z-axis is the combined fitness F

Stochastic Algorithms

We will consider algorithms which are based on randomization principle.

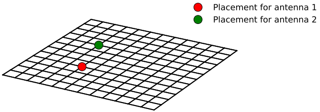
- Genetic Algorithm
- Evolutionary Strategy
- Simulated Annealing
- Hill Climbing

Each algorithm maintains a candidate solution or pool of candidate solutions called population

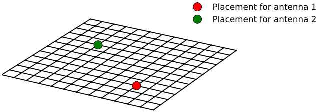
Stochastic Algorithms: Operand

Candidate solution or an **individual** is a member of a set of possible solutions.

- Simulated Annealing and Hill Climbing maintain single individual



- Genetic Algorithm and Evolutionary Strategy maintain a population of individuals



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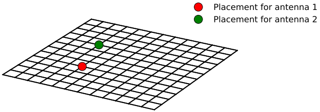
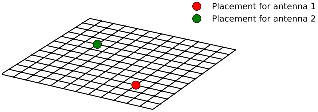
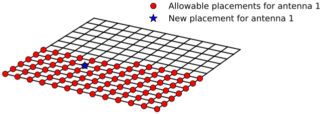


Stochastic Algorithms: Mutation Operator

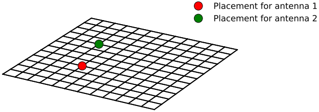
1. Given an individual, select an antenna uniformly at random, let's say antenna 1:



2. For antenna 1, select any other allowable placement:

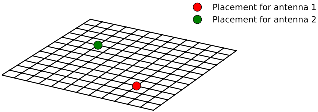


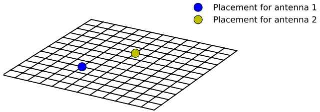
3. Change position for antenna 1 in individual:



Stochastic Algorithms: Crossover Operator

1. Select two individuals from population:

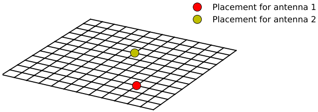


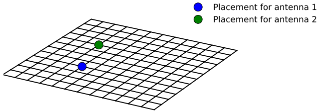


2. Select a crossover point, and swap placements prior to the point:

$$\begin{array}{lc|c} \text{ind}_1: & A_1 & A_2 \\ & \downarrow \;\; \uparrow & \\ \text{ind}_2: & A_1 & A_2 \end{array}$$

3. Two new offsprings created:





Genetic Algorithm

P $\leftarrow$ generate p random individuals. Compute $fitness(\mathbf{ind}_i), i \in [1,p]$;
$i = 0$;
while $i < gen_{max}$ **do**
- Elitism: Select n_e fittest individuals to add to **P'** ;
- **for** $(p - n_e)/2$ *times* **do**
  - /* 'select' returns a pair of individuals */
  - $\mathbf{M} \leftarrow select(\mathbf{P}, 2)$;
  - **if** $rand(0,1) < p_c$ **then**
    - $\mathbf{O} \leftarrow crossover(\mathbf{M})$;
    - Add O to P' ;
  - **else**
    - Add M to P' ;
- Uniformly select $p_m \cdot (p - n_e)$ individuals from P, and apply *mutation* operator to each ;
- Update $P \leftarrow P'$;
- Compute $fitness(\mathbf{ind}_i); i \in [1,p]$;
- Update $i \leftarrow i + 1$;

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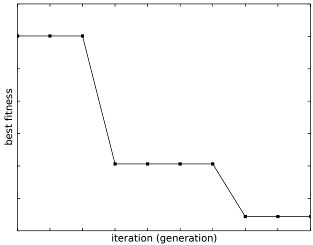

Plateaus suggesting stagnation of search

Evolutionary Strategy

P $\leftarrow$ generate μ random individuals ;

$i = 0$;

while $i < gen_{max}$ **do**

  Create λ/μ offsprings from each μ individuals by applying *mutation* operator;

  Add all offsprings to **P** ;

  Compute *fitness*($\mathbf{ind}_i$), $i \in [1, \lambda + \mu]$;

  Keep μ best individuals in **P**, and discard remaining $\lambda - \mu$ individuals ;

  Update $i \leftarrow i + 1$

Evolutionary Strategy

1 **P** ← generate μ random individuals ;

2 $i = 0$;

3 **while** $i < gen_{max}$ **do**

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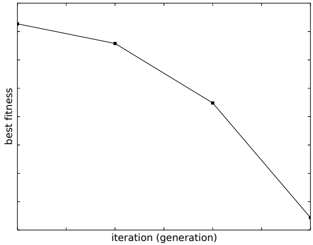

More mutations allow in-depth exploration of search space, and also makes rapid progress

Simulated Annealing

c $\leftarrow$ generate a random individual ;
$i = 0$;
while $i < i_max$ **do**
    n $\leftarrow$ $mutate(\mathbf{c})$;
    if $fitness(\mathbf{c}) < fitness(\mathbf{n})$ **then**
        if $rand(0,1) < e^{-\delta f / T}$ **then**
            `/* replace current individual by a higher fitness (less fitter) individual */`
            c $\leftarrow$ **n**
    else
        c $\leftarrow$ **n** ;
    $T \leftarrow T \cdot f_{cooling}$;
    $i \leftarrow i + 1$;

Simulated Annealing

c ← generate a random individual ;
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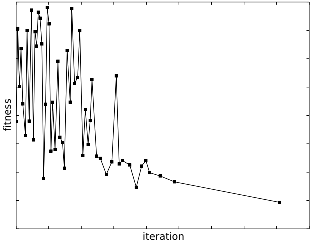

Fluctuation in fitness gradually reduces due to cooling

Hill Climbing

```
Initialize c ← generate a random inidividual ;
Compute fitness(c) ;
i = 0 ;
while i < i_max do
    n ← mutate(c) ;
    if fitness(n) < fitness(c) then
        c ← n
    i ← i + 1
```

Hill Climbing

Initialize **c** $\leftarrow$ generate a random inidividual ;
Compute $fitness(\mathbf{c})$;
$i = 0$;
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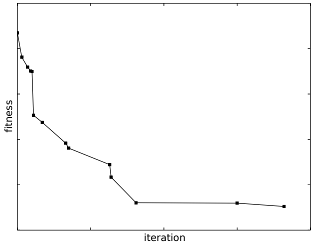


Greedy approach to accept only fitter(low fitness) individuals

Part 3: Evaluation of test cases

Experimental Setup

1. All test cases describe platforms which are representative of real-world use cases like mobile devices, trucks, and cars. If one were to scale up we will expect same behaviour to hold

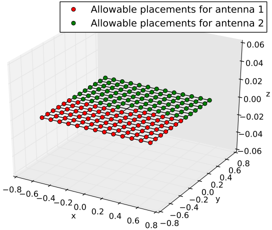
2. We use a popular *NEC2* simulator to get fitness parameters

3. Evaluated the entire search space using an exhaustive algorithm to find the optimal antenna locations which is not ordinarily possible

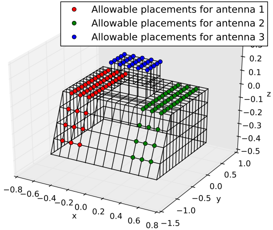
4. Termination criteria was set to be at most 50% evaluations of the search spcae

5. 10 independent runs of each test case against each algorithm with $\alpha = \beta = 1/2$

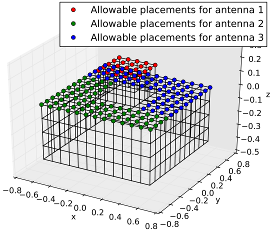
Experiments: Test Cases



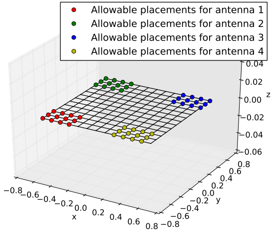
Test Case #1: search space size of 7056 (84*x*84) allowable placements



Test Case #2: search space size of 50625 (45*x*45*x*25) allowable placements

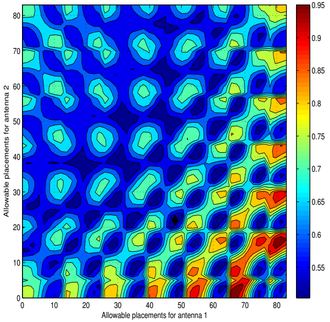


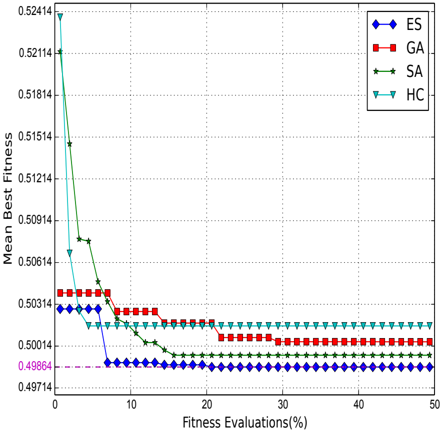
Test Case #3: search space size of 126025 (71*x*71*x*25) allowable placements



Test Case #4: search space size of 20736 (12*x*12*x*12*x*12) allowable placements

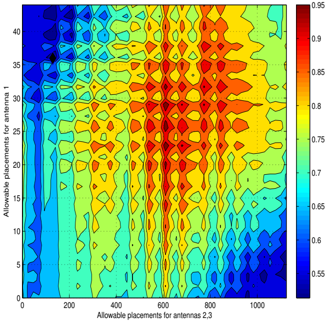
Results - Test Case 1

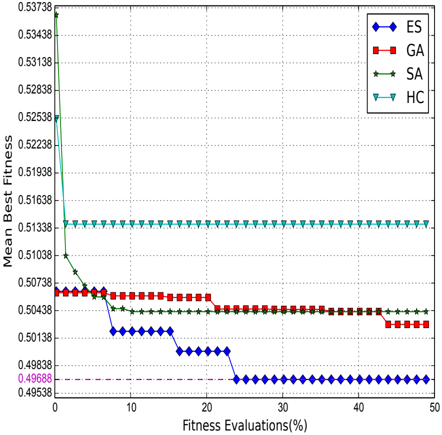




Algo.	% Evaluations		Best fitness	
	Mean	Error	Mean	Error
ES	6.80	6.08	0.49864	0.00000
GA	14.17	13.81	0.50031	0.00315
SA	8.58	4.07	0.49949	0.00161
HC	2.11	1.11	0.50159	0.00418

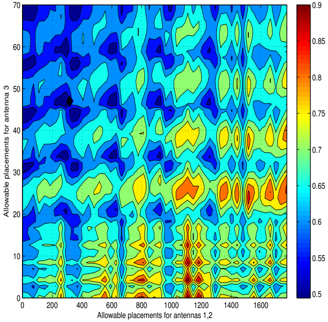
Results - Test Case 2

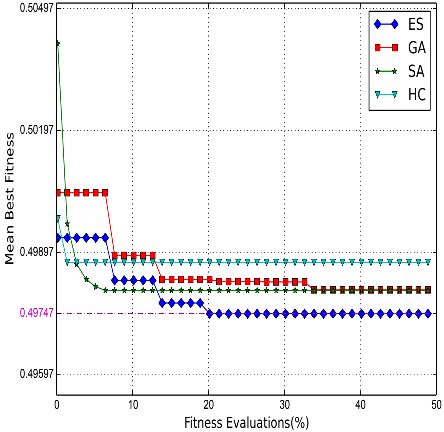




Algo.	% Evaluations		Best fitness	
	Mean	Error	Mean	Error
ES	14.45	9.28	0.49688	0.00000
GA	23.47	15.60	0.50288	0.00277
SA	3.27	2.80	0.50427	0.02218
HC	0.34	0.20	0.51380	0.01386

Results - Test Case 3





Algo.	% Evaluations		Best fitness	
	Mean	Error	Mean	Error
ES	14.66	4.00	0.49747	0.00000
GA	24.28	16.02	0.49773	0.00040
SA	3.87	1.82	0.49766	0.00038
HC	0.18	0.09	0.49873	0.00146

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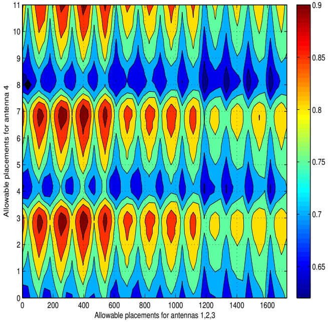
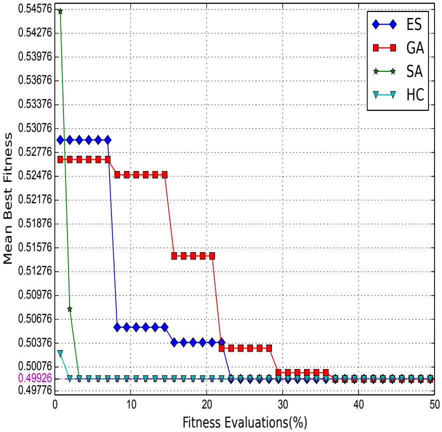
Results - Test Case 4

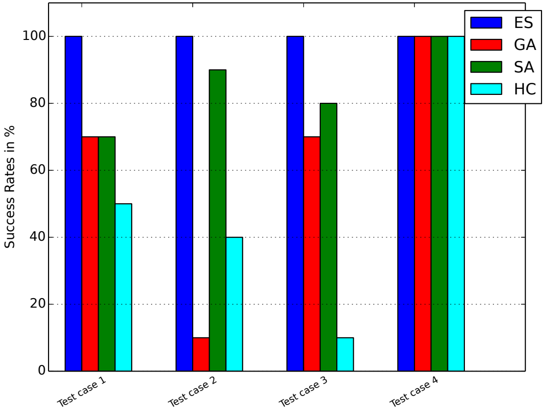


Algo.	% Evaluations		Best fitness	
	Mean	Error	Mean	Error
ES	14.11	6.17	0.49926	0.00000
GA	22.42	9.94	0.49926	0.00000
SA	2.19	0.78	0.49926	0.00000
HC	0.43	0.40	0.49926	0.00000



Results - Success Rates

Success rate report the percentage of runs in which the algorithm is able to find the optimum



Conclusion

- Formalized the antenna placement problem
- Generic problem formulation to accommodate multiple antennas and platforms
- Optimal placements found using Evolutionary Strategy with at most 25% evaluations of search space
- Future work - Consider other techniques like *Differential Evolution* and *ALPS*