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# Heuristic optimization techniques for self-orientation of directional antennas in long-distance point-to-point broadband networks

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ABSTRACT

A self-orientation system for a directional antenna is capable of determining the best orientation to receive the strongest wireless signal. In the event of two antennas being deployed randomly or deployed in a dense space where the effects of multipath and other wireless interference exist, efficient search algorithms are required to find the best orientation. Therefore, this paper presents four heuristic optimization techniques for the self-orientation of directional antennas in such events: Pattern Search method, Downhill Simplex method, DIRECT method, and Genetic Algorithm. The modification of each technique for this orientation problem is described, and the performance of each algorithm using different test cases with real world experiments is also described. From our study, we show that the Pattern Search method is the most suitable optimization technique for the self-orientation of directional antennas in long-distance point-to-point broadband networks.



## 1. Introduction

Recently, numerous research groups have started to focus on Directional Wireless Networks (DWNs) due to their superior ability to bridge a network over a very long distance [1–4]. With advantages of greater distances, much of this research have been conducted regarding the problem of area coverage in a DWN [2–4]. Not only that, directional antennas have also been beneficial in greatly reducing communication interferences from other electronics devices [5–7].

Although directional antennas have countless advantages as mentioned above, there are also the research challenges of how to determine the best orientation for the receiver or the transmitter since a directional antenna has a limited Field of View (FoV) [8]. If the two antennas being used for a point-to-point broadband network are deployed with predefined and known locations, it would not be difficult to determine the necessary orientations for the best connection as it is usually when the two antennas are facing each other. However, this way guarantees the best connection only when the antennas are operating in an open space where there is a direct Line-of-Sight (LoS) between the two antennas and there is no interference present [9]. In contrast, if two antennas are located in a dense space with no LoS, determining the orientation of the antennas becomes complicated as there may be other unpredictable orientations that can provide the best connection.

It is for this reason that we present four optimization techniques in this paper: Pattern Search method, Downhill Simplex method (Nelder–Mead method), DIRECT method, and Genetic Algorithm. Since these techniques do not require any knowledge of the objective function gradient

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and only require sampling points in the search domain, they are applicable in finding the best orientation in an unknown environment. Moreover, as each technique is a heuristic based search method which in general is capable of finding the global minimum, they are also applicable to a dense space where multiple local minima might exist.

We expect contributions of this paper would be found as follows. To the best of our knowledge, it is the first time that heuristic optimization techniques are used to rapidly establish a DWN. This research also presents how to modify the heuristic optimization techniques in order to apply them to the establishment problem. In addition, we evaluate the performance of these search techniques and find the one most suitable for determining the best orientation in an unknown environment and a dense space.

## 2. Related works

For a long time, the installation of a point-to-point network involved the use of a human intervention to adjust an antenna's orientation as well as additional tools to determine its best orientation; this was done as it is relatively low cost, and there is no need for a dedicated direction finding receiver [10–12]. In such way, the antenna is moved or rotated until the point of maximum signal strength is determined, most often based on received signal strength. As a result, this job often requires a long period time to determine the best orientation, and the network efficacy depends strongly on the skill level of the operator. Furthermore, accuracy might decrease rapidly as distance to the partner radio increases.

To reduce the time and effort needed to determine the best connection when using manual direction finding, approaches that incorporate antenna units with a GPS (Global Positioning System) or IMU (Inertial Measurement Unit) for mobile use have been introduced [13,14]. Also, for medium access control using directional antennas in ad hoc networks, the mobile nodes are assumed to know their physical locations as well as the locations of their neighbors through the use of GPS [15,16]. However, the antenna units equipped with this additional equipment are generally much more expensive. In addition, as those units can only work in outdoor environments and open spaces where GPS signals are easily received, the location functionality cannot be utilized in indoor environments where directional antennas have the potential to increase wireless capacity [9].

Also, previous research in directional wireless networks typically assumed the beam of each directional antenna can be steered to its intended sender or receiver [17]. However, it is hard to determine the best orientation for directional antennas due to the effects of multipath and the presence of other wireless interference.

To cope with such effects, several research groups have introduced rotatable directional antennas for direction of arrival (DoA) estimation [18–20]. Although those studies show the feasibility of self-orientation of directional antennas, they only dealt with one axis, i.e., the antenna scans to one axis: either vertical axis or horizontal axis. In order to maximize the advantages of using directional antennas for a wireless connection, the orientation of the antennas should be expressed in both the vertical and horizontal axis [8]. In addition, their methods involve an exhaustive scanning on all possible domains, it is very time consuming despite the fact that they would help to find the optimal direction.

## 3. Antenna orientation problem

Unlike an omni-directional antenna that has more of a torus sensing range, a directional antenna relies on a specific orientation to receive a quality Received Signal Strength Indication (RSSI). FoVs of a directional antenna, on both the horizontal and vertical planes, are narrower than those of an omni-directional antenna. Because of this, a directional antenna can transmit a wireless signal much further than an omni-directional antenna while consuming the same amount of energy. For the extended range to be beneficial, the antenna must be oriented in a specific angle and direction.

From the concept of the FoV, its sensing model can be viewed as a sector in a three-dimensional (3D) plane. The 3D directional sensing model is denoted by 2-tuple $(\boldsymbol{P}_i, \overrightarrow{\boldsymbol{O}_i}), i \in \{\mathrm{R}, \mathrm{T}\}$ as shown in Fig. 1, where R means a receiver, and T means a transmitter. In addition, $\boldsymbol{P}$ is the location $(x, y, z)$ of the directional antenna in a 3D plane, and $\overrightarrow{\boldsymbol{O}}$ is its sensing orientation. The sensing orientation $\overrightarrow{\boldsymbol{O}}$, is composed of $[\phi, \theta]^{\mathrm{T}}$, where the horizontal $\phi$ and vertical $\theta$ offset angles from the origin of the antenna. Using Friis Transmission Formula [21], we can formulate the transmitted and received power, $p_{\mathrm{T}}$ and $p_{\mathrm{R}}$, between two distant antennas by,

$$\frac{p_{\mathrm{R}}}{p_{\mathrm{T}}} = \left(\frac{\lambda}{4\pi \mathrm{O}r}\right)^2 G_{\mathrm{T}}(\overrightarrow{\boldsymbol{O}_{\mathrm{T}}}) G_{\mathrm{R}}(\overrightarrow{\boldsymbol{O}_{\mathrm{R}}}) \tag{1}$$

where $\lambda$ is a wavelength, O$r$ is a distance between two antennas, $G_{\mathrm{T}}$ is the transmitter gain in the direction $\overrightarrow{\boldsymbol{O}_{\mathrm{T}}}$ in which it sees the receiver, and $G_{\mathrm{R}}$ is the receiver gain in the direction $\overrightarrow{\boldsymbol{O}_{\mathrm{R}}}$ in which it sees the transmitter. Therefore, it can be seen from Eq. (1) that when the transmitter and the receiver are facing each other, the received power $p_{\mathrm{R}}$ will be maximized.

Now, we can assume that this sensing model would be applied to three cases. The first case is when a direct path is present between two antennas as depicted in Fig. 2a. In this case, it would not be difficult to determine the necessary orientations for the best connection as it is usually when the two antennas are pointing at each other. In contrast, if two antennas are located in a dense space with LoS (the second case) or no LoS (the third case) as depicted in Fig. 2b and c, discovering the orientation of the antennas is not trivial as there may be other unpredictable orientations that can provide the best. Actually, this results from the likelihood of a multipath effect due to signal reflection from surrounding objects as well as interferences from other electronics devices [9].

In the event of two antennas being deployed randomly where the sensing receiver does not know the transmitter's location or orientation, determining the direction of the receiver becomes more challenging. Given the complex and

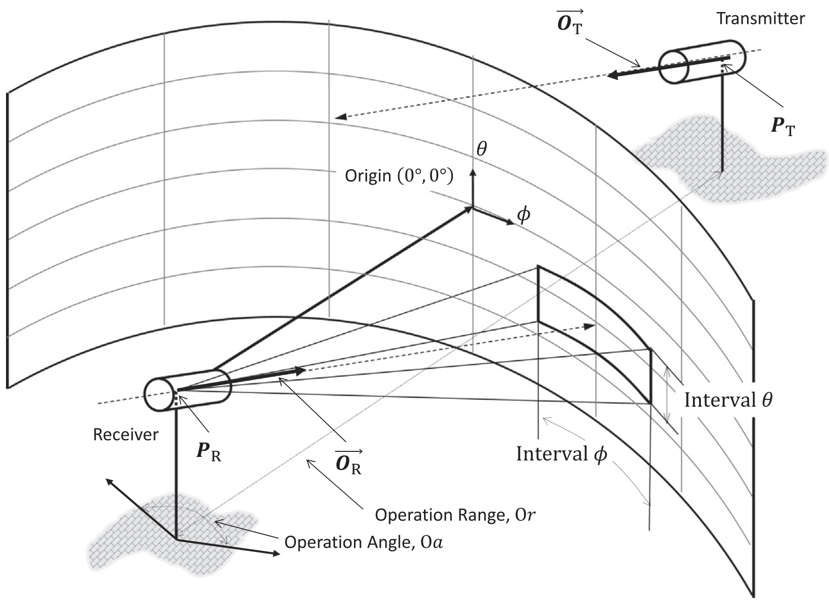
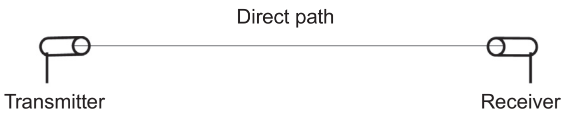
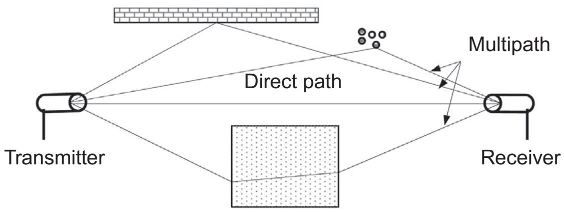


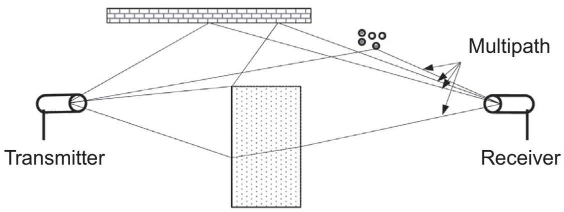

**Fig. 1.** The 3D directional sensing model.




(a) First case, direct path




(b) Second case, direct path with multipath




(c) Third case, multipath

**Fig. 2.** Statistical issues with signal strength measurement with directional antennas. (a) First case, direct path. (b) Second case, direct path with multipath. (c) Third case, multipath

numerous issues involved in point-to-point directional networks, there is a need for an appropriate search method for finding the correct orientation for a directional sensing antenna to receive the best possible signal.

## 4. Optimization of antenna orientation

### 4.1. Problem statement

Given two directional antennas with an initial random deployment, one configured as the fixed transmitter and the other as the rotatable receiver, sampling all possible points in the domain by the receiver may be the most accurate way to find the best orientation where the receiver obtains the maximized signal strength [9].

However, this approach is time-consuming due to the sampling of unnecessary points and would be inappropriate in a case that requires the rapid establishment of a wireless network. Thus, we set the objective of this paper as: to quickly and accurately find the best orientation to receive the best RSSI using search/optimization. The problem statement is then as follows:

$$\begin{aligned}&\text{Find} : \phi^*, \theta^*\\&\text{To minimize} : f(\phi, \theta)\\&\text{Subject to} : \phi_L \leqslant \phi \leqslant \phi_U, \theta_L \leqslant \theta \leqslant \theta_U\end{aligned} \tag{2}$$

where $\phi^*$ and $\theta^*$ are optimal roll and pitch angles of the receiving antenna. Therefore, $\phi$ and $\theta$ correspond to the design variables, i.e., $\mathbf{x} = [x_1, x_2]^T = [\phi, \theta]^T$; $\phi$ is a roll angle of the receiving antenna subject to $\phi_L \leqslant \phi \leqslant \phi_U$, and $\theta$ is a pitch angle of the receiving antenna subject to $\theta_L \leqslant \theta \leqslant \theta_U$. $f(\phi, \theta)$ is an objective function, producing a current RSSI measured at roll angle $\phi$ and pitch angle $\theta$. Thus, if the objective function is minimized, it can be said that the best orientation, composed of $\phi^*$ and $\theta^*$, for maximizing the signal strength is found.

Fig. 3 shows a flow chart of the antenna orientation problem, and in the following sections, we will describe optimization methods for finding optimal design variables.

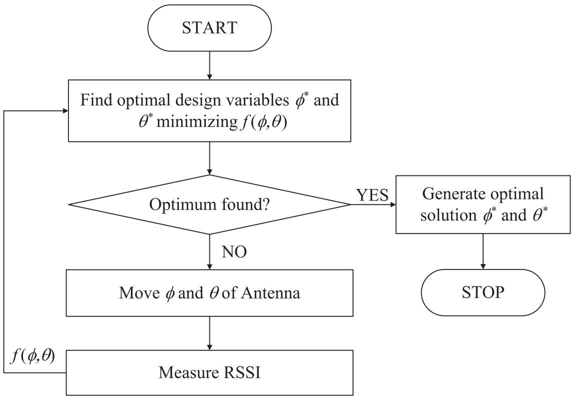



**Fig. 3.** Flow chart of antenna orientation problem.

### 4.2. Optimization techniques

Due to insufficient information which arises from the antennas random deployment, meaning they have no information on one another's location or orientation, generating an objective function $f(\mathbf{x})$ for predicting an optimal solution is impossible. This eliminates the possibility of using traditional optimization techniques such as the Steepest Descent method and the Broydon–Fletcher–Goldfarb–Shanno (BFGS) method, that generally require knowledge of the objective function gradient to find the minimum [22]. Not only that, as the receiver relies on a servomotor based pan-tilt system to alter its orientation, a certain interval angle on each horizontal and vertical direction is required. Due to these issues, the problem should be treated as a zero-order problem as well as an integer problem meaning the objective function is non-smooth.

Given the nature of this problem, we assume that the wireless signal strength is the same within a certain interval angle on each horizontal and vertical direction. This indicates that, for instance, if the interval is 15° on the horizontal direction, the strength of the wireless signal is the same between 0° and 15° (this region is illustrated with a bold rectangle in Fig. 1). Therefore, this assumption will allow the orientation problem to be a type of the integer problem and help to shorten the size of the search space when using heuristic optimization as well.

We have decided to use four heuristic optimization techniques which can be applied to the zero-order problem of antennas: Pattern Search method, Downhill Simplex method, DIRECT method, and Genetic Algorithm.

It is worth noting that the problem in this paper could be solved by some other optimization techniques such as Simulated Annealing (SA) and Ant-Colony Optimization (ACO). Nevertheless, we do not include them here as they might involve much more function evaluations than those that will be used in this paper [23,24]. Remember that the antenna orientation problem demands a fast convergence for a rapid establishment of directional networks.

#### 4.2.1. Pattern Search method

The Pattern Search method, also called the Hooke–Jeeves algorithm, is one of the representative direct search methods that samples points in the design space and uses the information it has obtained to decide, where to search next [25]. A fundamental concept of this method is to proceed with a series of explorations and pattern based moves to find the minimum. In the exploratory stage, the method sequentially performs exploratory moves on a single variable, holding all others constant. The method then performs a pattern move by altering all variables with the appropriate stored exploratory moves. These stages repeat until the minimum is found or the maximum number of function evaluations is met.

#### 4.2.2. Downhill Simplex method

The Downhill Simplex method is an iterative search technique for minimizing a function, developed by Jones Nelder et al. in 1965 [26]. The method uses the concept of a simplex, which is a polytope of $n+1$ vertices in n dimensions: a line segment in one dimension, a triangle in two dimensions, a tetrahedron in three-dimensional space and so forth.

The Downhill Simplex method entails a series of steps for moving the simplex downhill: *Reflection*, *Contraction*, *Expansion*, and *Shrinkage*. For each step, the method uses both data known from the current simplex location as well as data from previous moves to change the simplex size. The steps repeat until the size is small enough to contain the minimum.

#### 4.2.3. DIRECT method

The DIRECT method is known as a deterministic global optimization algorithm, developed by Jones et al. in 1993 [27,28]. The main idea of DIRECT method is to select rectangles likely to contain the global minimum in the design space. The basic process is to divide potentially-optimal rectangles into smaller rectangles and have the process repeat until a maximum number of function evaluations or a minimum rectangle size is met.

#### 4.2.4. Genetic Algorithm (GA)

The GA is a model of biological evolution based on Charles Darwin's theory of natural selection. The GA is essentially random search techniques and requires several operators such as the crossover, recombination, mutation, and selection. The details of these operators and the GA can be found in [29,30].

GA differs from the previous three optimization techniques in that it uses coding of the design variables and not the actual variables. Thus, the design variables in Eq. (2) are represented as a binary string as shown in Table 1.

In Table 1, all variables are discretized with

$$r_i = \frac{x_i^U - x_i^L}{(2^{b_i} - 1)} \tag{3}$$

where $x_i^U$ is the upper bound on variable, $x_i^L$ the lower bound on variable, $b_i$ the number of bits to code $x_i$ and $r_i$ is the resolution between discretized values of $x_i$.

**Table 1**
The design variables represented with a binary string.

| Variable | Bits | Lower bound | Upper bound | Resolution |
|---|---|---|---|---|
| $\mathbf{x} = [\phi, \theta]^T$ | 4 | 1 | 9 | 1 |

This alteration means that if the sensing antenna scans $\phi$ direction with 15° interval, subject to $-60° \leqslant \phi \leqslant 60°$, then the number of total points on this direction will be 9, and this interval results $r_1 = 0.53,\ x_1^L = 1,\ x_1^U = 9$, and $b_1 = 4$ (Note that we round the resolution $r_1 = 0.53$ to $r_1 = 1$ to make this problem an integer problem.).

Our implementation of GA uses a tournament selection method to randomly pick a small subset of chromosomes from the mating pool; the chromosome with the lowest cost in this subset becomes a parent. We use the uniform crossover where the first child receives a bit from the first parent with crossover probability $P_c$, and the second child receives a bit from the second parent. To examine new population for mutation, we randomly switch zeros and ones with a probability of mutation.

### 4.3. Modifications

In order to apply the four optimization techniques to the orientation problem in this paper, the following modifications are required. Table 2 shows a summary of their modifications, where "YES" indicates the method has been modified, and "NO" indicates the method has not been modified, respectively.

#### 4.3.1. Pseudo objective function

The DIRECT method was originally designed to solve problems subject to side constraints. For this reason, the problem statement defined in Eq. (2) can be used in the DIRECT method. However, other three optimization techniques were not originally designed to solve problems subject to side constraints. The problem statement must be in the form of unconstrained minimization so that the side constraints in Eq. (2) are converted to the form of inequality constraints like $g_i(\mathbf{x}) \leqslant 0$. Thus, the original problem statement is reformulated as follows:

$$\begin{aligned} &\text{Minimize} :: \Psi(\mathbf{x}) = f(\mathbf{x}) + \mathrm{P}(\mathbf{x}) \\ &\quad \text{where } \Psi(\mathbf{x}) \text{ is the pseudo objective function} \\ &\qquad f(\mathbf{x}) \text{ is the original objective function} \\ &\qquad \text{shown in Eq.(2)} \\ &\qquad \mathrm{P}(\mathbf{x}) \text{ is the exterior penalty function} \end{aligned} \tag{4}$$

where $\mathrm{P}(\mathbf{x}) = r_p \sum_{i=1}^{4} \max\,[0, g_i(\mathbf{x})]$ and $r_p$ is a penalty multiplier which determines the magnitude of the penalty for inequality constraint violations. From this modified statement, it is evident that $\mathrm{P}(\mathbf{x}) = 0$ if no constraints are violated. Violation of a constraint imposes a penalty $r_p$ proportional to the violation so that the minimization algorithm tends to avoid the violations. Thus, $r_p$ should be large enough to give a strong penalty to the pseudo objective function. One example is depicted in Fig. 4a, where the Downhill Simplex method tries to move *Reflection*. This selection violates the inequality constraint, $\theta_L \leqslant \theta$, so the pseudo objective function $\Psi(\mathbf{x})$ becomes 1000 due to the imposed penalty multiplier $r_p$, set to 1000.

#### 4.3.2. Integer programming

These four techniques were not originally intended for use with an integer problem. Therefore, we truncate two design variables from every step so that the new truncated values form integer values. This modification will be applied to all methods and is illustrated in Fig. 4b.

#### 4.3.3. Choice of initial points

The Pattern Search method and Downhill Simplex method are very sensitive to the initial points chosen and can be easily trapped in a local minima. To combat this, we chose four different initial points to make up for this limitation and improve the accuracy of their search. The four points, one in each quadrant of the search domain, are depicted in Fig. 4c. Note that the Downhill Simplex method generally requires three initial points. The objective function values at four vertices, $f(\mathbf{x}^0)$, $f(\mathbf{x}^1)$, $f(\mathbf{x}^2)$, and $f(\mathbf{x}^3)$, are evaluated, and the lowest point is excluded from the possible simplex. The other remaining points are identified as highest point $\mathbf{x}^h$, second-highest point $\mathbf{x}^s$, and lowest point $\mathbf{x}^l$. Then, this modified approach returns to normal.

#### 4.3.4. Termination criteria

The four optimization techniques are not guaranteed to converge, even for smooth problems.

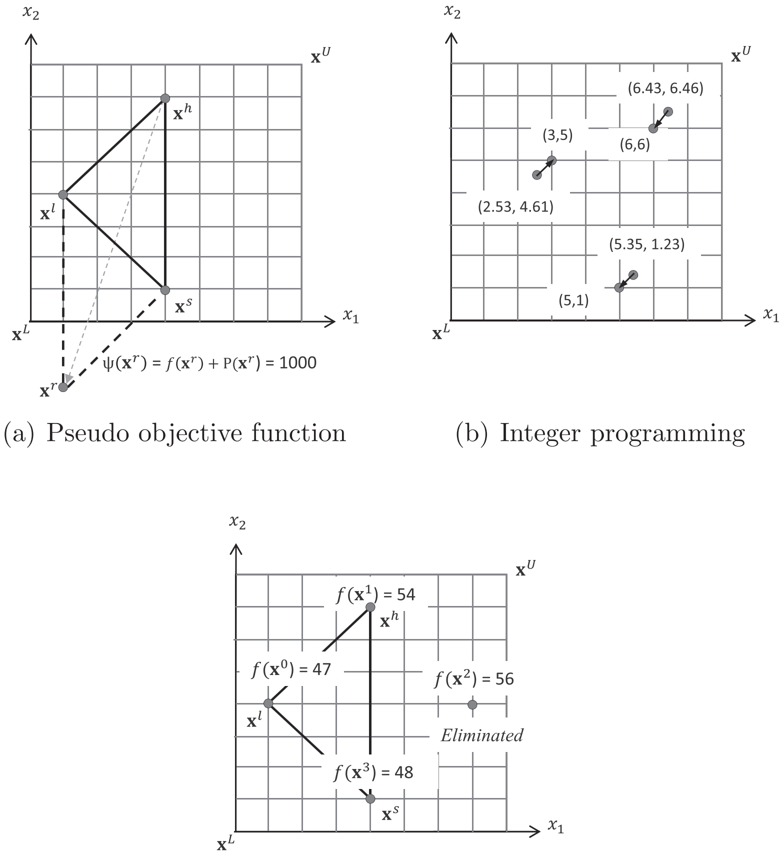
$$\frac{f(\mathbf{x}^h) - f(\mathbf{x}^l)}{1 + |f(\mathbf{x}^l)|} \leqslant \varepsilon \text{ or } \sqrt{\frac{1}{n}\sum_{i=0}^{n}\left[f(\mathbf{x}^i) - \bar{f}\right]^2} \leqslant \varepsilon, \text{ where } \bar{f} = \frac{1}{n}\sum_{i=0}^{n} f(\mathbf{x}^i). \tag{5}$$

Eq. (5) is the termination criteria used for the Downhill Simplex method, where $\varepsilon$ is a specified tolerance. The first criteria in Eq. (5) is satisfied when a decrease in $f(\mathbf{x})$ over the entire simplex is small, and the second criteria will be satisfied when the standard deviation of $f(\mathbf{x})$ over the entire simplex is small. In addition, if the number of function evaluations $q$ exceeds some large pre-specified number $q_{\max}$, then the search process will end. For the Pattern Search method and DIRECT method, the end of two sequential minimizations is compared as their termination criteria, i.e. convergence is indicated if

$$|f(\mathbf{x}^q) - f(\mathbf{x}^{q-1})| \leqslant \varepsilon. \tag{6}$$

**Table 2**
Summary of modifications of four optimization techniques.

| Optimization Technique | Pseudo objective function | Integer programming | Choice of initial points | Termination criteria |
|---|---|---|---|---|
| Pattern Search method | YES | YES | YES | YES |
| Downhill Simplex method | YES | YES | YES | YES |
| DIRECT method | NO | YES | NO | YES |
| Genetic Algorithm | YES | YES | NO | YES |




(a) Pseudo objective function (b) Integer programming

(c) Choice of initial points

**Fig. 4.** Modifications of the optimization techniques for the antenna orientation problem. (a) Pseudo objective function. (b) Integer programming. (c) Choice of initial points.

For the Pattern Search method and DIRECT method, the maximum number of function evaluations is also included. GA is stopped after no further improvement, meaning GA can be stopped if chromosomes become homogeneous. Thus, we define termination bit string affinity value $b_{\max}$.

## 5. Experiments

### 5.1. Setup

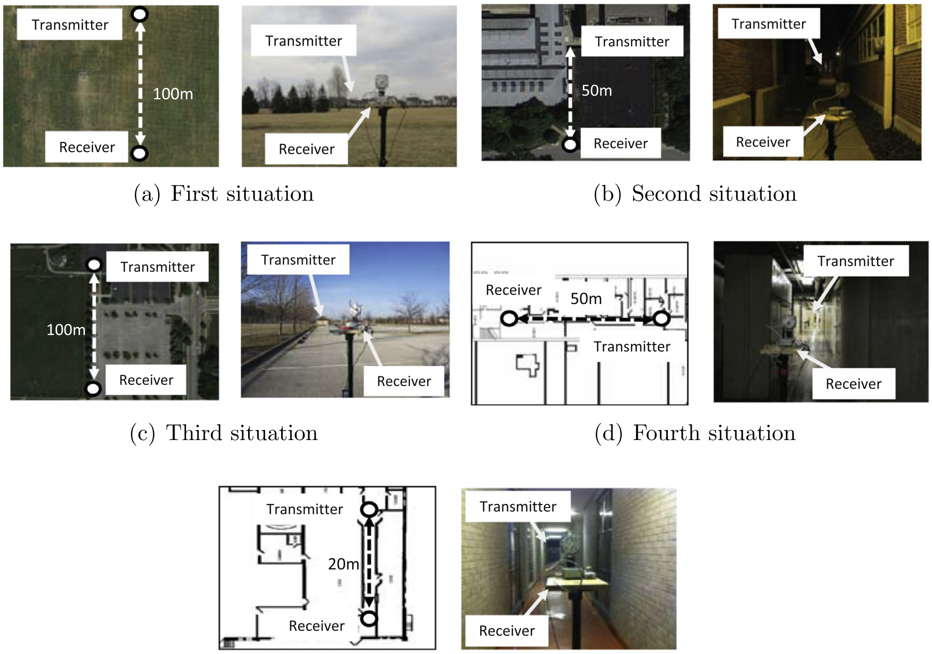
To validate the performance of the optimization techniques discussed in this paper, we conducted real world experiments with directional antennas available from PCTEL [31], shown in Fig. 5a and b. We used MYP24015PTNF as a transmitter and MYP24010PTNF as a receiver. Both devices are directional antennas, have 10-dBi of gain, and use the 2.4 GHz frequency range. The first antenna has a 30° horizontal and vertical beamwidth at 1/2 power and the latter has a 55° horizontal and vertical beamwidth at 1/2 power. In addition, to automatically find the maximum RSSI available, we have built a custom pan-tilt system having two DoF (Degree-of-Freedom) using two servomotors. This system was then incorporated into the receiver antenna as shown in Fig. 5c.

We prepared five different situations, as shown in Fig. 6. Fig. 6a shows the first situation where the two antennas are deployed in an outdoor environment representative of the first case shown in Fig. 2a. Fig. 6b shows the second situation where the two antennas are deployed in an outdoor environment representative of the second case shown in Fig. 2b. Fig. 6c shows the third situation where the two antennas are deployed in an outdoor environment representative of the third case shown in Fig. 2c. In Fig. 6a–c, all left images show maps from Google Earth depicting our test areas, and all right figures show pictures of the actual experiments. In Fig. 6c, the arrow designated "Transmitter" indicates the physical location of the antenna which was located behind a building and was no LoS. In addition to outdoor experiments, we conducted indoor experiments as they are the fourth and fifth situations respectively as shown in Fig. 6d and e. All left images in Fig. 6d and e show a floor plan depicting our test areas, and all right images show pictures of the actual experiments.

We set up the interval as 15° on each axis, subject to each constraint, $-60° \leqslant \phi \leqslant 60°$ and $-60° \leqslant \theta \leqslant 60°$. Therefore, the design space becomes $x_1$ and $x_2$ $\in \{-60°, -45°, -30°, -15°, 0°, 15°, 30°, 45°, 60°\}$ and the number of elements in each domain becomes 9. For

(a) Transmitter (b) Receiver (c) Pan-tilt servo device

**Fig. 5.** PCTEL directional antennas [31]; (a) MYP24015PTNF, (b) MYP24010PTNF, and (c) Pan-tilt servo device that we built for this study. (a) Transmitter. (b) Receiver. (c) Pan-tilt servo device.




(a) First situation (b) Second situation

(c) Third situation (d) Fourth situation

(e) Fifth situation

**Fig. 6.** Deployment of antennas in five different situations: (a)–(c) Real-world experiments conducted in outdoor environments; (d) and (e) Real-world experiments conducted in indoor environments. (a) First situation. (b) Second situation. (c) Third situation. (d) Fourth situation. (e) Fifth situation.

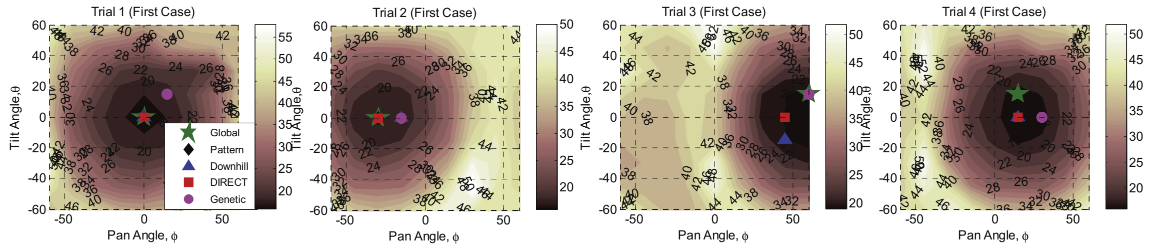
experiments with a fair evaluation, each algorithm was run with four different trials from the five situations. Thus, there are a total of twenty trials for the entire experiment. In each trial, the orientation of the transmitter $\vec{\boldsymbol{O}}_T$ was fixed to roughly face the receiver, and the initial orientation of the receiver was set randomly but was bound $\vec{\boldsymbol{O}}_T$ and $\vec{\boldsymbol{O}}_R$ to the operation angle ($Oa = 120°$).

Table 3 shows the optimization algorithm settings which were selected according to the results of a preliminary parametric study carried out individually with each algorithm. In Table 3, initial step size is used in the first exploratory stage to perform exploratory moves for the Pattern Search method. $\alpha$,$\beta$,$\gamma$, and $\delta$ are a selection of four coefficients in the Downhill Simplex method and correspond to *Reflection* coefficient, *Contraction* coefficient, *Expansion* coefficient, and *Shrinkage* coefficient, respectively.

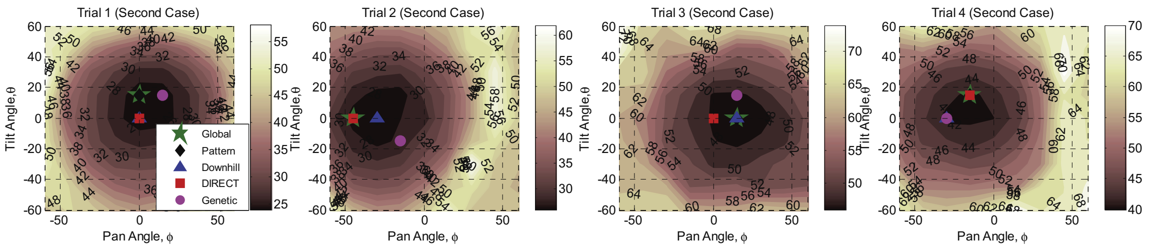
The four optimization methods are computationally expensive which means more objective function evaluations are necessary while finding the solution. In other words, the more objective function evaluations are taken, the slower convergence rates are manifest. In addition, each technique is a heuristic based search method, meaning they do not guarantee finding a global minimum. Therefore, we compare the performance of each algorithm using different

**Table 3**
Optimization technique settings.

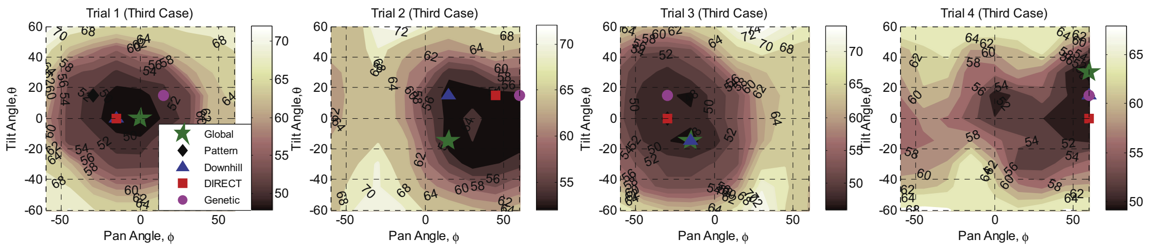
| Optimization technique | Parameters |
|---|---|
| Pattern Search method | initial step size = 1, $\varepsilon = 1 \times 10^{-2}$, $q_{max} = 20$,$r_p = 1000$ |
| Downhill Simplex method | $\alpha = 1.0$, $\beta = 0.5$, $\gamma = 2.0$, $\delta = 0.5$, $\varepsilon = 1 \times 10^{-2}$, $q_{max} = 20$, $r_p = 1000$ |
| DIRECT method | $\varepsilon = 1 \times 10^{-2}$, $q_{max} = 20$ |
| Genetic Algorithm | population size = 4, mutation rate = 1%, $P_c = 50\%$, $b_{max} = 95\%$, $r_p = 1000$ |



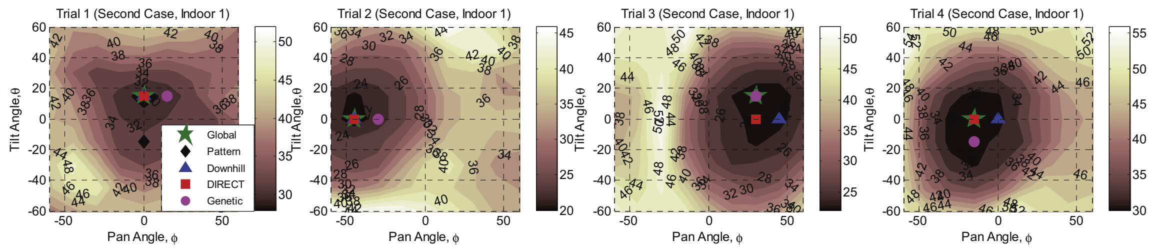

(a) First situation



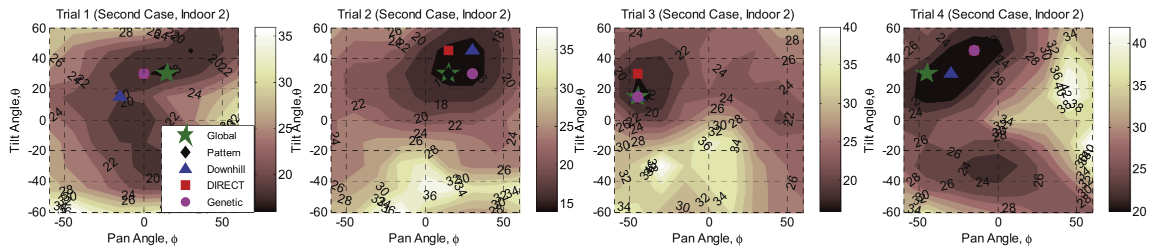

(b) Second situation




(c) Third situation




(d) Fourth situation




(e) Fifth situation

**Fig. 7.** 20 trials conducted from five different situations in an unknown environment. A video file demonstrating each algorithm with one of the trials can be found at http://web.ics.purdue.edu/~minb/research/broadband/video1.wmv. (a) First situation. (b) Second situation. (c) Third situation. (d) Fourth situation. (e) Fifth situation.

test cases with real world experiments to test three factors: (1) the number of function evaluations, (2) the elapsed time from initiative to the convergence of algorithm, and (3) the accuracy of finding the global solution.

For the function evaluation, it will be considered only in the case that the algorithm searched a new grid. It means that if one algorithm needs to evaluate a certain grid multiple times, these multiple evaluations are counted only once. This rule will be applied to all of the algorithms. Due to ever-changing RSSI patterns [1,32,33], we allow a tolerance of +1 dB for accuracy evaluation when considering whether the result produced by the method is correct or not. Also, we gather RSSI values 20 times at each point and average them for use as the current $f(\mathbf{x})$ to reduce the effect of ever-changing RSSI. From these evaluation factors, we can investigate which algorithm is suitable for the rapid establishment of DWNs.

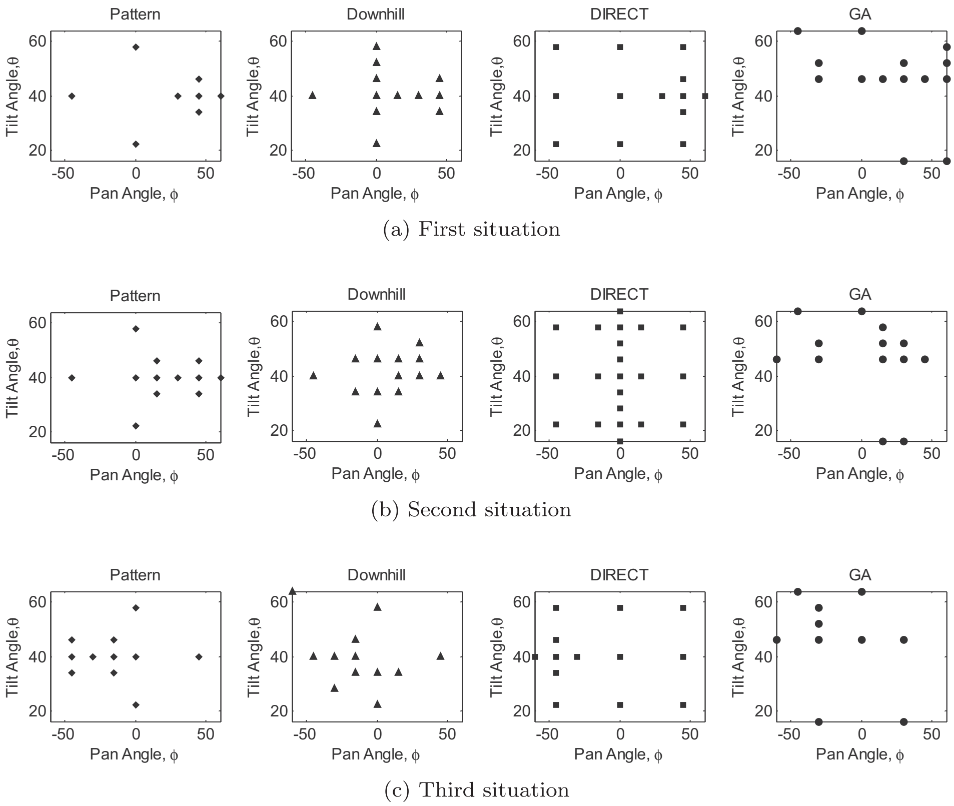
In order to identify the best orientation in advance, we scanned all possible points from every trial, and then we began testing with the four optimization methods. With these procedures, if one optimization method indicates the same location as the best in all scanned points, it can be said that the method is validated in terms of finding the global minimum.

### 5.2. Results

Contours in Fig. 7 show all scanned RSSI values at all points in the five different situations as depicted in Fig. 6 as well as the solutions found by each algorithm. Lower and darker value of the contours means a better RSSI in Fig. 7. This means that the smallest value (or the darkest spot) produced by the location of $\phi$ and $\theta$ indicates the best orientation. As we expected to see in the contours, there are mostly explicit patterns showing convex shapes around the minimum as well as some additional distortion to these patterns seen elsewhere. This implies that the minimum can be found by the heuristic optimization techniques introduced in this paper. Also, it is shown that when there is only one direct path presented, there is only one local minimum that is also the global minimum as shown in Fig. 7a. On the other hand, when there is a multipath signal presented, there are often accompanying multiple local minima as shown in Fig. 7b–e.

The solutions found by each algorithm are depicted in Fig. 7. In these figures, the location of the global minimum is marked with "★", locations of the solutions found by the Pattern Search method, Downhill Simplex method, DIRECT method, and GA are marked with "◇", "△", "□", and "○", respectively. As depicted in these figures, the solutions found by the methods lie in and around the global minimum. This validated that all methods used in this paper were suitable and well designed for this self-orientation problem.

The 12 sub-figures in Fig. 8 are from the first trial of the three situations in an outdoor environment and represent traces left by each method when finding the solution. Note that if we sum up the number of all traces in each figure,




(a) First situation

(b) Second situation

(c) Third situation

**Fig. 8.** Traces left by each method when finding the solution in outdoor environment. (a) First situation. (b) Second situation. (c) Third situation.

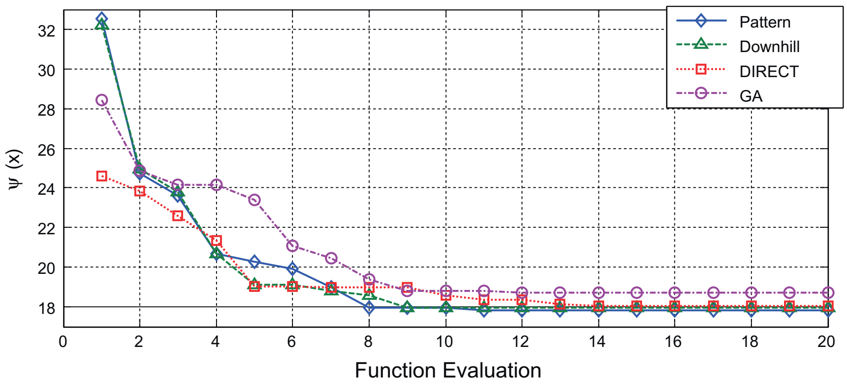



**Fig. 9.** The best objective as a function evaluation. These results were averaged over 20 different trials.

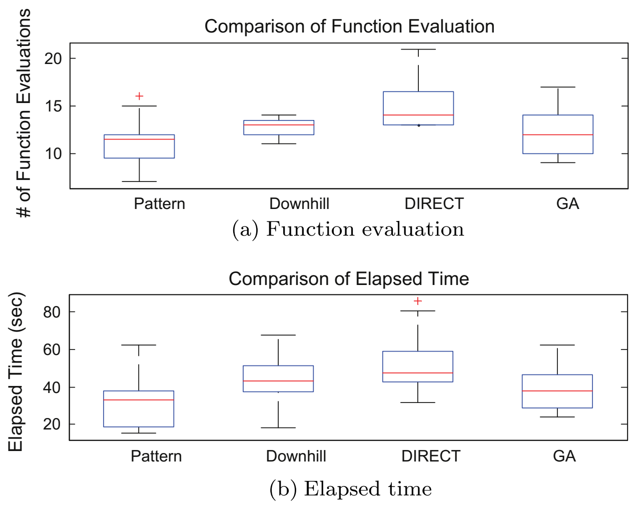



**Fig. 10.** A summary of results on the number of function evaluations and elapsed times to converge to the solutions. (a) Function evaluation. (b) Elapsed time.

**Table 4**
Summary of averaged results from 20 trials.

| Evaluation criteria | Pattern Search method | Downhill Simplex method | DIRECT method | GA |
|---|---|---|---|---|
| Number of function evaluations | 11.30 | 12.75 | 15.15 | 12.25 |
| Elapsed time (sec) | 33.82 | 43.58 | 53.49 | 39.25 |
| Accuracy (tolerance of +1 dB) | 18/20 (90%) | 18/20 (90%) | 19/20 (95%) | 16/20 (80%) |

that number represents the number of function evaluations. As shown in traces left by the Pattern Search method and the Downhill Simplex method, there were always four scanned points in each quadrant of the search domain. This modification resulted in the choice of an initial point from the initial four points which helped in reducing the total number of function evaluations when finding the global minimum. We can also see that the GA finds the minimum by random search locations, and the other three methods find the minimum through the use of a certain search patterns.

The results of an average of the best objectives over the 20 trials versus the number of function evaluations necessary are shown in Fig. 9. As shown in the figure, each objective converges as the number of function evaluations increases. This validates all methods are suitable to finding an acceptable solution. The figure also shows that the GA was the last to approach the solutions as well as had the worst accuracy as compared to the other three methods. This slow convergence seems to be due to its essentially random search technique in unknown environments. The DIRECT method approached the solutions slightly faster than GA but ultimately was the last to find a solution. The Pattern Search method and the Downhill Simplex method both converged on the objective faster than the others (See the values between the 8th and 10th function evaluations.), but ultimately the Pattern Search method was the fastest by a thin margin. Thus, the Pattern Search method outperformed all other methods when it came to the convergence rate of finding the solution.

Fig. 10a and b graphically summarize the results over the 20 trials on the number of function evaluations and the measured elapsed time. As expected, these two factors show almost the same results, i.e., the fewer objective function evaluations were taken, the faster elapsed times were shown. From Fig. 10, it is shown that out of all test, the Pattern Search method took the shortest time to find the solution, followed by the GA. The DIRECT method took much longer in all situations. This result shows that the DIRECT method is not suitable for rapid deployment.

Table 4 shows a summary of the results that three evaluation factors were averaged over the 20 trials. As numerical values in the first and second rows show, the Pattern Search method requires the fewest function evaluations and is the fastest method among the other three methods. When it comes to evaluating accuracy, the DIRECT method shows the best performance by finding the global solution 19 times of the total 20 trials. The Pattern Search method and Downhill Simplex method found the solution 18 times of the total 20 trials, and GA found the solution 16 times out of the total 20 trials. Therefore, all methods show more than 80% of accuracy when finding the solution. The DIRECT method shows 95% of accuracy and can be said to have the highest accuracy from its exhaustive search and far more function evaluations when compared to the other three methods.

## 6. Conclusion

In this paper, the four heuristic optimization techniques: Pattern Search method, Downhill Simplex method, DIRECT method, and GA, were presented and applied to the problem of finding the best orientation of directional antennas.

From a set of experiments we conducted, acceptable orientations were found by each of the four methods. This validates all methods used in this paper as suitable and well designed for the self-orientation problem. From our performance evaluations, there was little difference in the accuracy of the system when using the different search methods as the solutions found by each lied in or around the global minimum. Because of this, the comparison of accuracy between the methods became a less important factor in determining the best method of finding the strongest wireless signal. Instead, from our comparison of the elapsed time and the function evaluations, we found that the Pattern Search method performs significantly better than the DIRECT method and slightly better than the Downhill Simplex method the GA.

Finally, we conclude from this research that the Pattern Search method is the most suitable optimization technique for the rapid establishment of a long-distance point-to-point sensor network connection. We believe that the flexibility this research provides is useful in many areas. For instance, this research could be used in a disaster area where previously established networks are destroyed, as well as in the rapid deployment of a wireless network needed by first responders for communication and data gathering.

In future work, we will consider employing some other evolutionary-based optimization algorithms that have been recently introduced such as Particle of Swarm Optimization (PSO). Also, we will use mobile robots capable of carrying directional antennas to extend this research to more complex environments where mobile antennas are required for a wireless connection.

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