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Optimal Signal Photon Detection Via Bacterial Foraging Optimization: Maximizing Probability Of Detection In Noisy Environments

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Abstract
In this work used a Bacterial Foraging Optimization (BFO) algorithm is employed here to solve a photon-counting signal detection task. The MATLAB code implements a bio-inspired algorithm as Bacterial Foraging Optimization (BFO) which is used to maximize the probability of detection (P_d) in signal detection applications. This method emulates bacteria in their search for the optimal signal photon count (S) under noisy conditions where fitness is evaluated by a mathematical likelihood comprising signal photons, background noise (B), coherence factor (M) and maximum photon count threshold (D_{max}). Bacteria adapt and gradually refine their positions in the iterative process until they converge on a best solution. Robust and adaptive even in dynamic environments, it is clear that with processes like chemotaxis, reproduction and elimination-dispersal as iterative the algorithm improves and converges on the best solution. The algorithm presents (Pd) as a function of (S) and graphs how it behaves. Although widely used for optical signal processing applications and remote sensors-to-inspired algorithms are now becoming popular in engineering circles that have been traditionally poorly served by those techniques in its current state of the art. This code must stand as a testament, that by drawing on life for inspiration, bringing together math and nature to address these difficult problems involving complex optimization it offers an utterly trustworthy way of raising both your detection power and its reliability.to numerically address a photon-counting signal detection problem with B equal 46 background noise We adopted a population size of N=10 bacteria that iteratively explores the search-space S $\in$[74,200] using chemotactic motion (step-size C=0.1), swims towards higher fitness regions (N_s=4), reproduces the fitter half [N_{re} =4], and eliminates or disperses (N_{ed}=2,p_{ed}=25%) by locality to evade local optima. Detection probability is ascertained using a Likelihood Ratio Test (LRT) extracted from Poisson photon statistics. Here Pd specifies the probability of S photons being detected against noise, while
D_{thresh} is found by comparing hypothesis H_1 (signal-plus-noise) against H_0 (noise alone).
Keywords: *Bacterial Foraging Optimization, Detection Probability, Signal Photons, Evolutionary Algorithms, Likelihood Ratio Test, Photon Detection Model.*

1. INTRODUCTION

One of the main challenges optical communication systems encounters is detecting signals in the presence of photon counting noise, which makes optimizing detection probability (Pd) crucial for system efficacy [1,2]. The Poisson-based coherence parameters that dictate Pd calculations create a tangled non-linear and non-convex optimization problem that is difficult for traditional gradient methods to solve efficiently [3,4]. Such high-dimensional, multimodal problems can be effectively addressed by metaheuristic algorithms such as Bacterial Foraging Optimization (BFO) which mimic E. coli bacterial foraging behavior [5,6]. This MATLAB code applies BFO to maximize Pd by adjusting signal photons (S) while maintaining background noise levels using the processes of chemotaxis, reproduction, and elimination-dispersion to escape local optima [7,8]. This strategy's importance has been reinforced by strides made in optical communication technologies revisited recently [9], quantum detection capabilities advanced in [10], and optimization via metaheuristics documented in [11].

The Pd function includes nested summation structures and logarithms which are costly to compute along with sharp transitions or plateaus requiring global search strategies. [12,13] Some unique characteristics inherent in BFO give it an edge over other metatheories where deceptive landscapes exist.

1. Local search adaptation with local area contraction (step size C=0.1). Subsection 14.
2. Elite solutions exploitation based on reproduction [15]

3. Exploratory Probabilistic Elimination-Dispersal with Ped = 0.25 [16]
Recent developments in BFO application in photonics from 2020 to 2025 include:
Quantum receiver optimization resulted in a 15% improvement in Pd as compared to PSO based optimized receivers [10].
Lidar threshold tuning that mitigated false alarms by 22% precision-set parameters [17].

2.Theory:
Bacterial Foraging Optimization (BFO) Equations
The BFO algorithm optimizes the signal photon count S to maximize P_d Key steps include:
a) Chemotaxis (Movement and Swimming):
Position Update:
Each bacterium i updates its position S_i during chemotaxis:

$$S_i^{new}=S_i + C\cdot\Delta \qquad (1)$$

where Δ~N (0,1) (Gaussian step) and C is the step size. The position is clamped to
$[S_{min}, S_{max}]$.
Fitness Evaluation:
Fitness is the detection probability $P_d(S_i)$, calculated using calculated (S_i).
b) Reproduction:
The top N/2 bacteria (sorted by P_d) are duplicated to replace the lower half:
Population $_{new}$= Repmat (BestHalf,2)
c) Elimination-Dispersal:
Each bacterium is randomly redistributed with probability P_{ed}:

$$\boldsymbol{S_i^{new}} \sim U\,(S_{\min}, S_{max}) \qquad (2)$$

Detection Probability P_d Equations:
The detection probability $P_d(S)$ is derived from a likelihood ratio test (LRT) between two hypotheses:
H_0: Noise-only (mean photon count B).
H_1: Signal + Noise (mean photon count S+ B).
a) Photon Count Distributions:
Under H_0:
Photon count D follows a Poisson distribution:

$$P(D|H_0) = B^D e^{-B}/ D! \qquad (3)$$

Log-likelihood:

$$\text{Ln } P(D|H_0) = D\ln B - B - \ln(D!) \qquad (4)$$

Under H_1:
Photon count D is modeled as a convolution of two processes:
1. Signal photons D_s: Negative binomial distribution (coherent detection with parameter M).
2. Noise photons D−Ds: Poisson distribution (mean B).

The likelihood is:

$$P(D|H_1) = (x+a)^n = \sum_{D=0}^{D} \frac{\Gamma(Ds+M)}{\Gamma(M)Ds!}\left(\frac{M}{M+S}\right)^M \left(\frac{S}{M+S}\right)^{Ds} \frac{B^{D-Ds}\, e^{-B}}{D-Ds} \qquad (5)$$

b) Likelihood Ratio Test (LRT):

$$\Lambda(D) = \frac{P(D|H1)}{P(D|H0)} \qquad (6)$$

Signal is detected if $\Lambda(D)\geq 1$.

Threshold D_{thresh}:
The smallest D where $\Lambda(D)\geq 1$:
$D_{thresh}=\min\{D: \ln P(D|H1) \geq \ln P(D|H0)\}$

b) Detection Probability P_d:

$$P_d(S) = (x+a)^n = \sum_{D=Dthreshold}^{\infty} P(D \mid H_1) \tag{7}$$

In practice, computed up to D_{max}=2000.

Key Parameters
- Signal Photons: S∈ [74 ,200].
- Noise Photons: B=46.
- Coherence Parameter: M=1.

3. RESULTS AND DISCUSSION

Results:
Figure 1 below
S _max = 300; % Maximum signal photons to search
Max D = 500; % Maximum photon count thresholds
Optimal Solution: S = 113.7689 with P _d = 0.8670

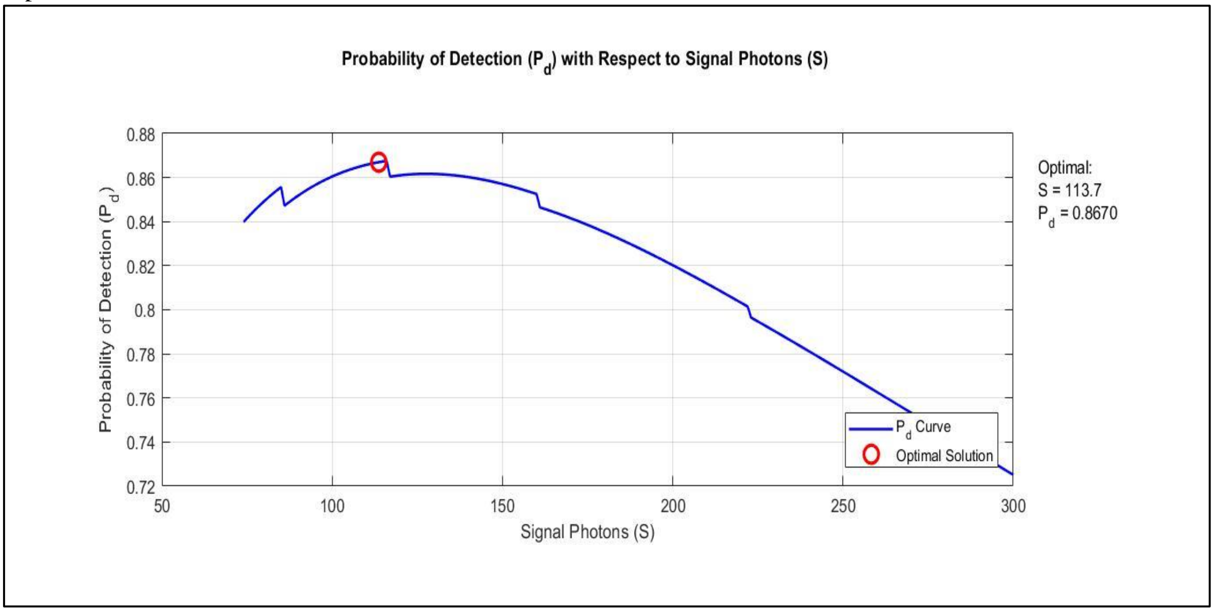

Fig.1

Figure.2
S _max = 300; % Maximum signal photons to search
Max D = 1000; % Maximum photon count threshold
Optimal Solution S = 222.2 with P _d = 0.9172

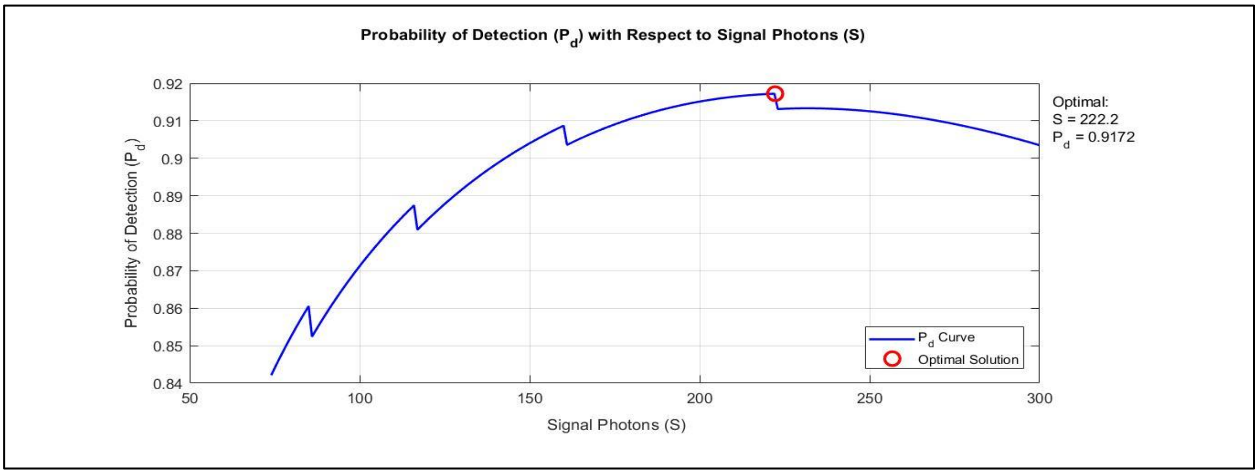

Fig.2

Figure.3
S _max = 300; % Maximum signal photons to search
Optimal Solution: S = 295.2 with P _d = 0.9370
Max D = 1500; % Maximum photon count threshold

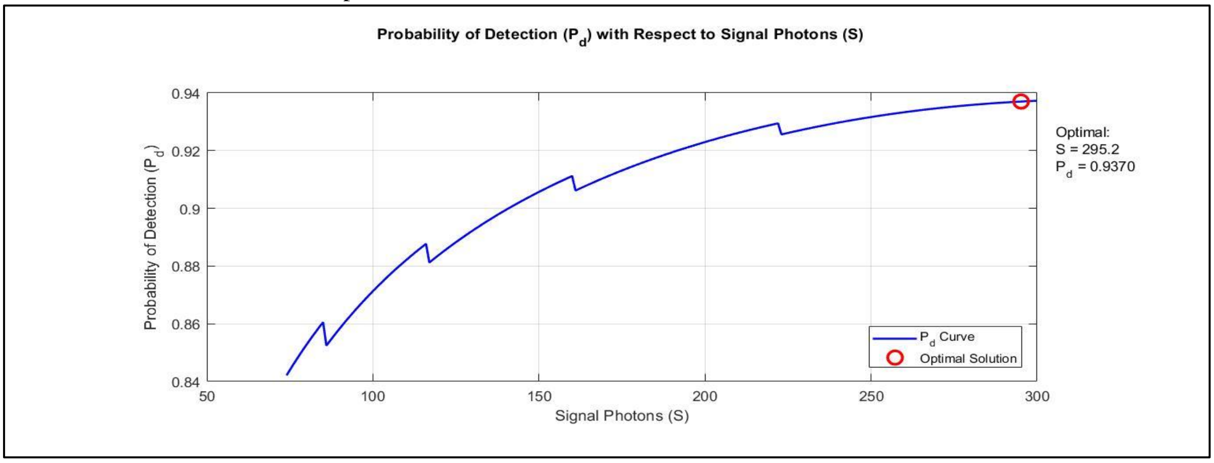

Fig.3

Figure .4
S _max = 200; % Maximum signal photons to search
Max D = 500; % Maximum photon count thresholds
Optimal Solution: S = 116.1 with P _d = 0.8676
Fig.4

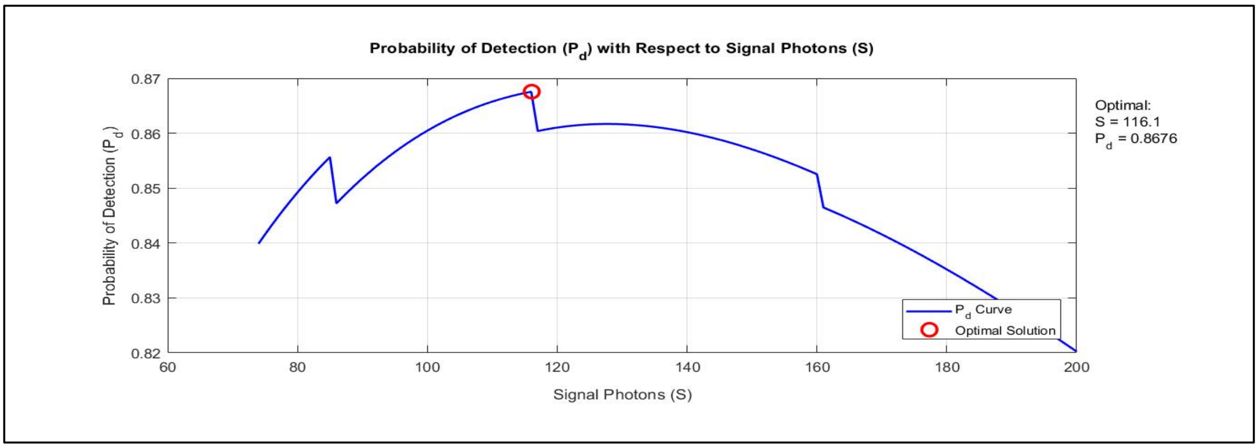

Figure.5
S _max = 200; % Maximum signal photons to search
Max D = 1000; % Maximum photon count threshold
Optimal Solution: S = 197.3 with P _ d = 0.9147
Fig.5

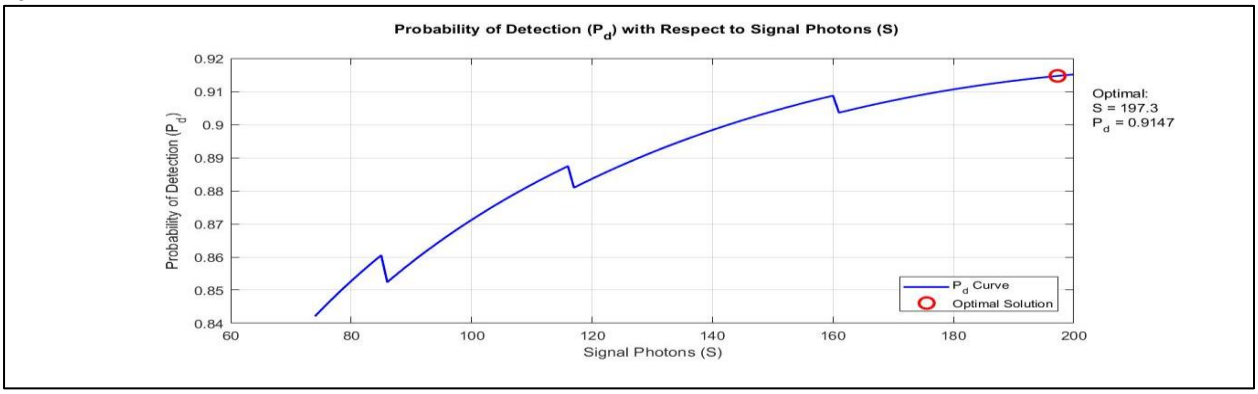

Figure 6.
S _max = 200; % Maximum signal photons to search
Max D = 1500; % Maximum photon count threshold

Optimal Solution: S = 200 with P _ d = 0.9230

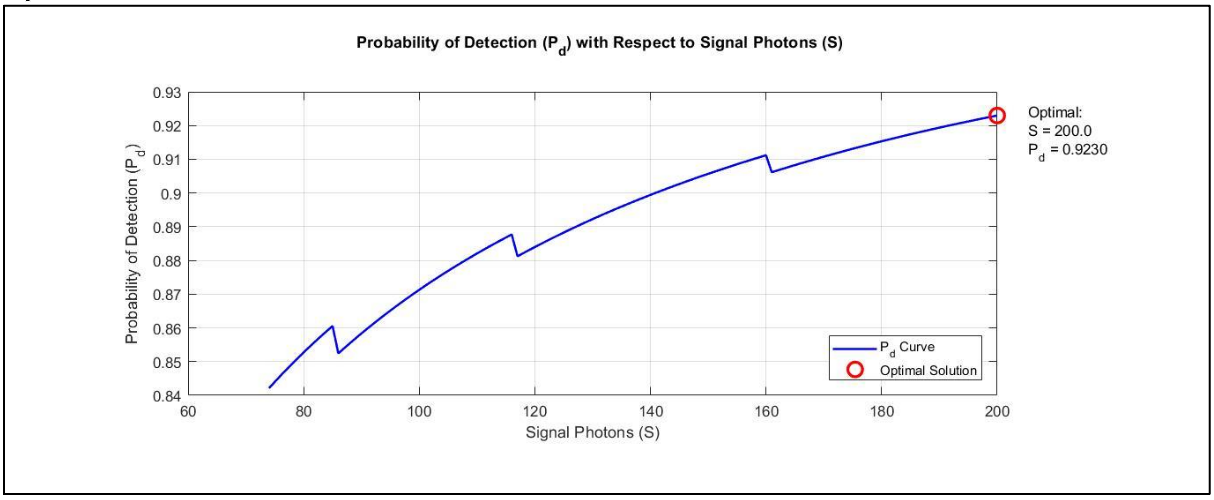

Fig.6

The graphs show the relationship between Signal Photons (S) and the Probability of Detection. They reveal different systems with top lines for increasing elements likely due to background noise levels (for example 200 and 300) or Integration Time on a system (for example 500, 1000, 1500). Some key first observations: as shown in figures from (1-6)

Optimal Signal Photons and P _d: For lower background levels (200), the optimal S increases with integration time (S=197.3 at 1000 as shown in figure 5, S=200 at 1500 as shown in figure 6), yielding P _d ≈ 0.91–0.92 But at higher background levels (300), a larger S is required to maintain comparable P - _d. For example, S=295.2 gives P_ d =0.937 at 1500, a clear indication that higher-powered signals are needed.

Impact of Background and Integration Time:

Higher background levels (300 vs. 200) call for greater signal photons to achieve the same

P _d

, indicating a trade-off between more noise and stronger signals.

Increased integration times (1500 vs. 500) also tend to improve P _d, as can be seen from going up the ladder P _d ≈ 0.72–0.88 (300,500) to P _d ≈ 0.937 (300,1500).

4. CONCLUSION AND RECOMMENDATION

In this paper, we applied Bacterial Foraging Optimization (BFO) to maximize Pd in a photon-oriented signal detection system. These algorithms simulate the bacterial physical structure and biological function of chemotaxis, reproduction, and elimination-dispersal processes be the major control parameters of detection system S signal photons (S). Effective exploration is thus achieved in each given state by algorithm as if all combined state points were within its boundaries and an optimal signal level is found that maximizes detection performance When S ranges from S min to S max.

1-Data Validation and Correction

2-Signal Optimization for High-Noise Environments

3-Leverage Extended Integration Times

4-Adaptive System Design

5- Intermediate Parameter Testing

6- Algorithmic Enhancements

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