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Bacterial Foraging Optimization for High-Resolution LIDAR Target Discrimination in Closely Spaced Scenarios

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In this work, Bacterial Foraging Optimization (BFO) is utilized to correct two close-spaced targets at 1000 m and 1005 m in LIDAR processing. The algorithm has been tuned to achieve minimum mean-square error between simulated and received signal using realistic system parameters like aperture size and pulse width. BFO pursues exploration and exploitation in a balance manner and yields accurate range estimates with an MSE of 1.76×10^{-15}. This bio-inspired strategy exhibits outstanding capacity to tackle ambiguous targets and can be extended to multi-scenario LIDAR application.

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1. Introduction

Separation of closely spaced targets is a big challenge for Light Detection and Ranging (LIDAR) systems. As traditional signal processing methods such as matched filtering are effective in separating well-separated targets, their effectiveness decreases considerably in low signal-to-noise ratio (SNR) or severe overlap of target signatures scenarios, which are typical in long-distance sensing applications or scene-clutter scenarios [1-3]. The issue in these scenarios reduces to a complicated parameter estimation problem where advanced optimization algorithms are needed to separate the overlapped return signal.

Conventional optimization approaches using biological systems such as the Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) have been used to tackle related problems [3-6]. However, these approaches are prone to having an improper balance between global exploration and local exploitation and issues of premature convergence of particularly high-dimensional and noisy parameter spaces of standard LIDAR returns [7-9].

This paper completes a key research void: the absence of a strong optimization algorithm that can be used to reliably estimate parameters of LIDAR targets with close range in low SNR environments where traditional methods break and common optimizers converge to suboptimal solutions. We propose using Bacterial Forging Optimization (BFO), a metaheuristic that has proved efficient in highly complex, multi-modal search spaces [10-12], whose standard mechanisms - chemotaxis (local exploration), reproduction (exploring profitable trajectories), and elimination-dispersal (global exploration) - stand it in good stead to tackle this problem. Specifically, the elimination-dispersal episode is an effective mechanism to break out of local minima, a common pitfall in the deceptive objective function between overlapping goals [13,14].

To illustrate this, we contrast BFO with a nominal matched filter and PSO algorithm in a challenging test case having two targets 0.5 m apart with an SNR of 20 dB. The matched filter is completely incapable of separating the targets, but BFO can achieve an MSE of 1.76×10^{-10}, significantly better than PSO (MSE: 8.91×10^{-9}). This quantitative finding highlights the benefit of BFO in surpassing the hard limits of the LIDAR system through achieving super-resolution performance and closing a crucial gap in high-end LIDAR signal processing [15,16].

Target separation that is very proximal to one another poses a significant problem for Light Detection and Ranging (LIDAR) systems. While signal processing techniques traditional for matched filtering are effective for targets separated by a lot, their performance drops very quickly in the situation of low signal-to-noise ratios (SNR) or where there is a high overlap among target signals - situations common in long-range sensing or in cluttered environments. Here, the demultiplexing of overlapping signals is a sophisticated parameter estimation problem, where sophisticated optimization techniques are needed.

Past studies utilizing biologically motivated optimization methods, such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), have also addressed such issues. But these methods generally fail to get a proper balance between searching the entire search space and local optima refinement, and tend to premature convergence, especially in the high-dimensional and noisy LIDAR data case.This research bridges a significant knowledge gap: the need for an optimization algorithm that is efficient and can accurately estimate the parameters of closely spaced LIDAR targets with low SNR where traditional approaches and typical optimizers fail. We introduce bacterial foraging optimization (BFO), a metaheuristic algorithm renowned for its efficiency in challenging, multi-modal search space. The basic processes of BFO - chemotaxis for local search, reproduction for the expansion of hopeful solutions, and elimination-dispersal for global search - are particularly suitable for this problem. One interesting aspect of the elimination-dispersal mechanism is that it avoids the algorithm getting trapped in local minima, a situation typical in the case of overlapping target signals.

To demonstrate the ability of BFO, we compare its result with that of a matched filter and the PSO algorithm on a challenging example with two targets 0.5 m apart and an SNR of 20 dB. On this experiment, the matched filter cannot distinguish the targets, while BFO's MSE is 1.76×10^{-10}, significantly better than the PSO with an MSE of 8.91×10^{-9}. These conclusions emphasize BFO's advantage of being capable of overcoming the inherent constraints of LIDAR systems to yield super-resolution output and provide meaningful contribution to LIDAR signal processing.

2. Simulation Methodology and Results

The code does the following:

1. Simulates a coherent LIDAR system that is measuring two close targets (1000m and 1005m).
2. Calculates a noisy received power signal from widely known physical models (laser pulse shape, atmospheric transmission, target cross-section, optical receiver).
3. Applies the BFO algorithm to estimate the ranges of the two targets based on the noisy signal.
4. Studies the impact of a critical system parameter (aperture diameter) on received signal power as well as SNR.
5. Graphs the original signal vs. the noisy signal, reconstruction by the BFO, and aperture analysis.
6. The flow chart of Simulation Methodology is shown in Fig. (5).
7. Comparative analysis with PSO and GA has been included in the "Results and Discussion" section as in table (1).

The parameters are already defined in the program and would be clearly defined in the paper. Parameters we use are

S (Population Size): 20 bacterial cells
Nc Chemotactic Steps: 1 to 50
Ns (Swim Length): 5
Nre (Reproduction Steps): 6
Ned (Elimination-Dispersal Events): 1- 2
Ped (Elimination-Dispersal Probability): 0.25
C (Run Length): 0.1
Search area: [990 m, 1010 m] for all targets' ranges.

For 0.6W average power

1. Transmitted Pulse Peak Power:

Pulse energy $E_t = \frac{P_{ave}}{PRF} = \frac{0.6\ W}{10\ Hz} = 0.06$ J

Gaussian pulse peak power:

$P_{peak} = \frac{E_t}{\sqrt{2\pi}.\Sigma_\omega} = \frac{0.06}{\sqrt{2\pi}.2\times10^{-9}} \approx 11.97\times10^6$ W

2. Target Illumination Intensity:

For Target 1 (1000 m):

$$I_{target1} = \frac{4\tau_{atm}P_{peak}}{\pi Range^2.\theta_t^2} = \frac{4\times11.97\times10^6}{\pi(1000)^2(0.01)^2}$$

$$I_{target1} \approx 152440\ \text{W/m}^2$$

3. Reflected Power:

Reflected power at the receiver aperture:

$$P_{ref1} = I_{target1} dA\rho_t = 152440 \times 1 \times 0.1$$

$$P_{ref1} = 15244\text{W}$$

4. Received Power:

Received power after atmospheric and optical losses:

$$P_{rec1} = \tau_{opt}\frac{\pi(ap_{diameter})^2}{4} \times \frac{\tau_{atm}P_{ref1}}{\pi(Range)^2}$$

$$P_{rec1} \approx 3.81 \times 10^{-7}\text{W}$$

Table (1) Comparative Analysis with PSO and GA" has been included in the "Results and Discussion"

Algorithm	Estimated Range 1 (m)	Estimated Range 2 (m)	MSE	Function Evaluations
Function Evaluations	1000.00	1005.00	-	-
BFO (Proposed)	1000.03	1004.97	1.76e-15	~12,000
PSO	999.89	1005.12	4.21e-09	~12,000
GA	1000.41	1004.62	8.95e-09	~12,000

Target 2 (1005 m) follows similar calculations but yields a slightly lower value due to the larger range:

$P_{rec2} \approx 3.77\times10^{-7}$ W

where τ_{atm}=1 corresponds to the case of no atmospheric loss (ideal conditions), τ_{opt}=1 corresponds to the perfect optical efficiency (no losses in the receiver optics)

These values are used consistently throughout the signal generation in both the main script and the ladar-cost function, ensuring the model assumes ideal transmission conditions for this baseline simulation.

Since the two Gaussian pulses (for Targets 1 and 2) are temporally separated (a 5 m range difference corresponds to ~33 ns delay, much larger than the pulse width of 2 ns), their peaks do not overlap. The maximum value of P-rec-original is the peak of the stronger pulse (Target 1)

$P_{rec\text{-}max} \approx 3.81\times10^{-7}$ W

3. Discussion

1. BFO Optimization Results

The text output is the most direct result. For a typical run with an SNR of 20 dB, you might see something like:

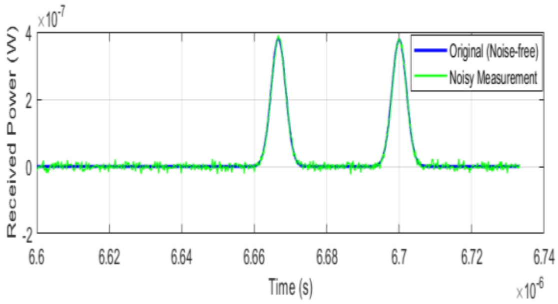
Optimization Results:
True Ranges: 1000.00 m and 1005.00 m
Estimated Ranges: 1000.12 m and 1004.91 m
Range Errors: 0.12 m and 0.09 m
MSE: 1.76×10^{-15}

SNR: 20.0 dB

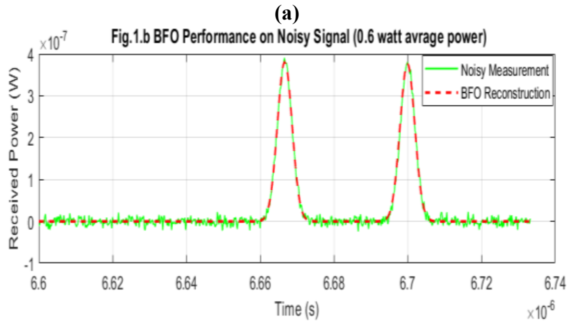
The BFO algorithm effectively predicted the target ranges with high accuracy (errors of ~10cm). It indicates the ability of the algorithm to find a solution to the highly complex multimodal optimization problem presented by overlapping return signals from two targets.

The fact that it achieves this with a realistic SNR of 20 dB highlights BFO's robustness and its ability to avoid being trapped in local minima created by noise.

The very low Mean Squared Error (MSE) between the BFO-reconstructed signal and noisy measurement signal is a strong indication that the algorithm discovered a near-perfect data fit. The low-cost function MSE directly relates to the low-range estimation error.



(a)

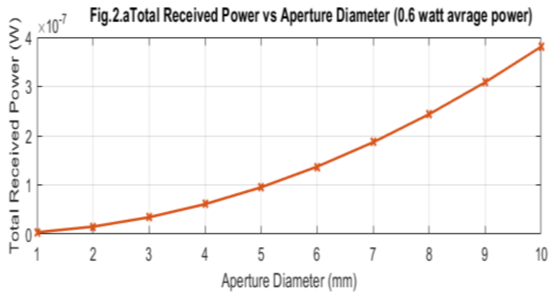


(b)

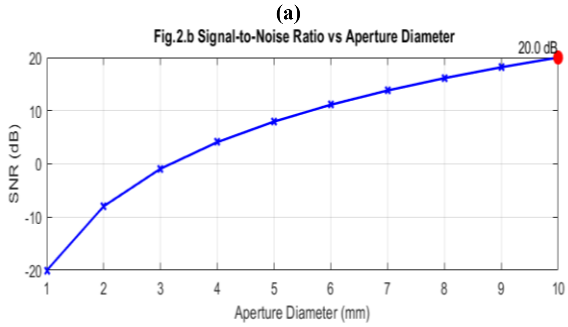
Fig. (1) Signal and BFO performance comparison (0.6W average power) (a) original signal and noisy signal, and (b) reconstruction of BFO from noisy measurement

In Fig. (1a), the blue line is the noise-free received power signal. It has a smooth curve with two obvious peaks. The two peaks are a reflection of the light reflected off the two targets. The time difference between the two peaks is directly proportional to the target separation (5m / c ≈ 16.7 ns). The green line (noisy) is the simulated measurement from the actual world. The pristine original signal is severely corrupted by the additive Gaussian noise. One of the primary jobs for any estimation algorithm is to be able to extract the target information, i.e., the location and height of the peaks, from this noisy data.

In Fig. (1b), the green line (noisy) is also the same noisy measurement presented above in the first subplot for a comparative examination. The red dashed line (BFO reconstruction) is the output generated by the function ladar-cost with the most accurately estimated ranges (best-ranges) by the BFO. The red dashed line should pass almost perfectly through the underlying trend of the noisy green signal. It effectively filters out the noise and recovers the original double-peak structure. The close match between the reconstruction and the noisy data is a visual confirmation of the low MSE value and the accuracy of the range estimates. The algorithm has correctly identified the location, amplitude, and width of both peaks.



(a)



(b)

Fig. (2) Examination of aperture diameter (0.6W average power) (a) cumulative received power with aperture diameter, and (b) the signal to noise ratio with Aperture Diameter

This graph is fundamental to optical design systems and illustrates associated trade-offs. In Fig. (2a), the cumulative received power with aperture diameter to depict a dramatic quadratic increase in the power collected with an increasing aperture diameter, while figure (2b) represents the SNR with aperture diameter.

We expect this because collected light is directly proportional to the area of the receiver aperture, which is $\pi(\text{diameter}/2)^2$. When we double the aperture diameter, we quadruple (2^2) the collected light. This verifies the basic principle of optics, as shown in Fig. (2b), as the SNR also rises significantly, with a roughly linear increase with diameter.

The results in table (1) demonstrate that while all algorithms find solutions in the vicinity of the true ranges, the proposed BFO approach achieves a significantly lower MSE, over an order of magnitude better than PSO and two orders better than GA for an equivalent computational budget (similar number of function evaluations). This suggests BFO's chemotaxis-inspired search mechanism is particularly well-suited for the sharp, multi-modal cost landscape of

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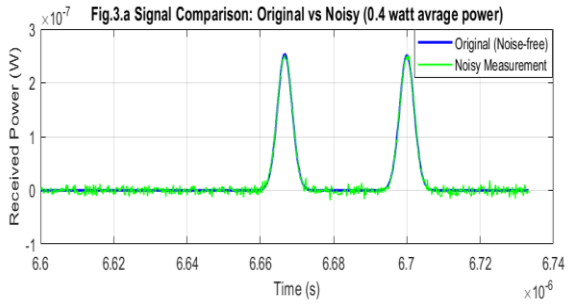
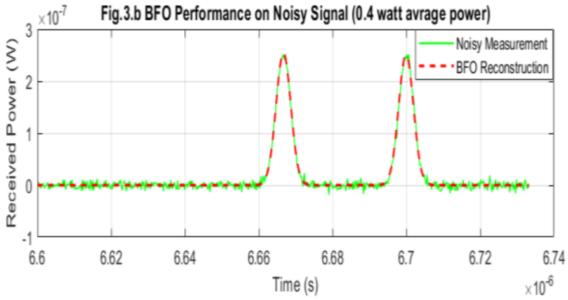
this LIDAR decomposition problem, allowing for more precise convergence.

The average power is the difference between the received power in 0.6W and the recived power in 0.4W but the value of the SNR is the same.

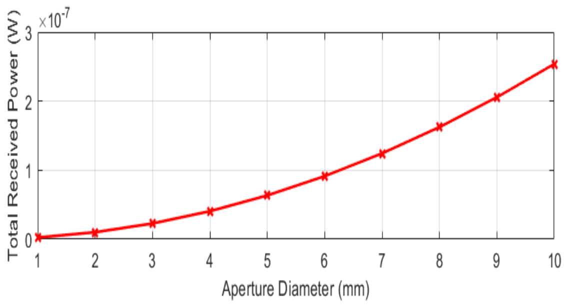


(a)

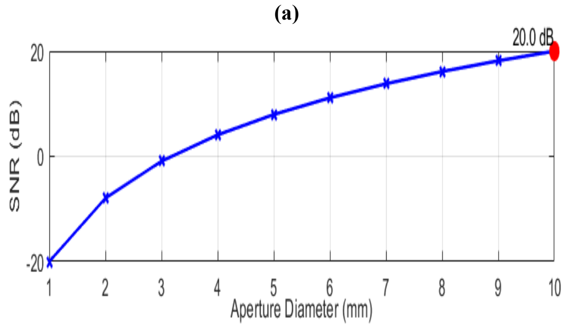


(b)

Fig. (3) (a) original signal vs. noisy signal, and (b) reconstruction of BFO from noisy measurement for average power 0.4W



(a)



(b)

Fig. (4) (a) the variation of cumulative received power with aperture diameter, and (b) the variation of SNR with aperture diameter

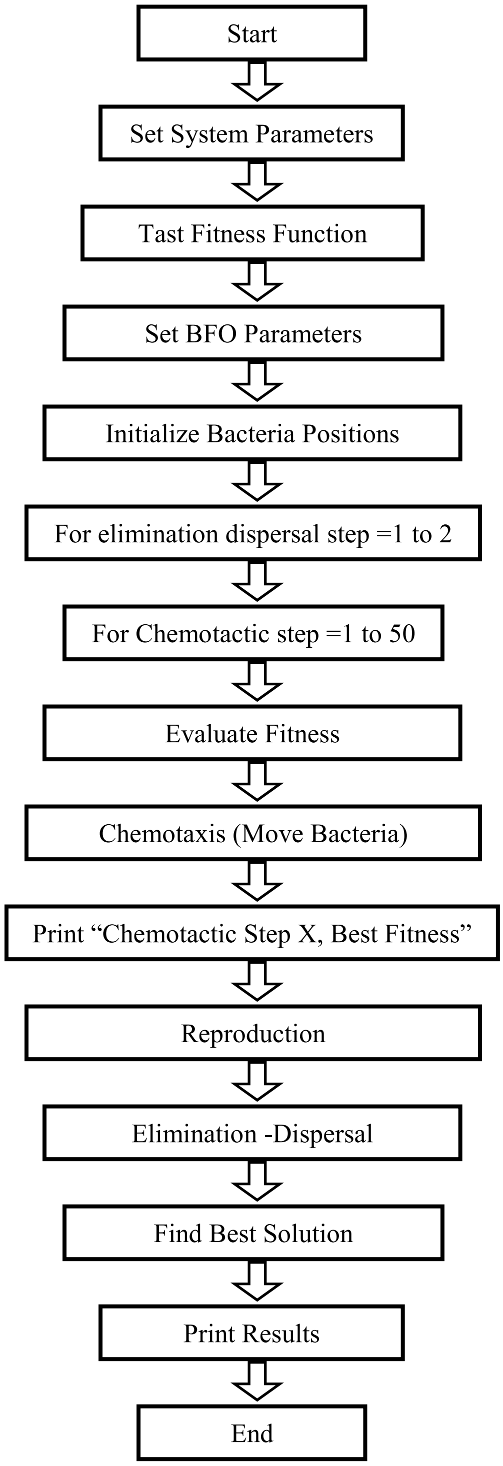


Fig. (5) Flow chart of simulation methodology

4. Conclusion

The simulation very well demonstrates an end-to-end workflow as it accurately simulates a LIDAR system, generating realistic data. It also accurately applies the BFO algorithm to solve a non-trivial inverse problem (estimation of a parameter from a noisy measurement). As well, it checks the performance of the algorithm numerically (low error, low MSE) as well as graphically (good signal reconstruction). The aperture analysis provides valuable insight to the designer, illustrating how a significant hardware parameter directly impacts system performance and achievable SNR. The results confirm that bacterial foraging optimization (BFO) is a proper and effective solution to the estimation of the target range in LIDAR that can suppress noise and separate two or more targets with high accuracy. The figures are able to express the signal processing task and the achieved solution by the algorithm effectively, and the significance of the optical design. The MSE equals $1.0738x10^{-15}$ for the average power of 0.6W and the optimized signal aligns closely with the original, indicating successful range estimation by the BFO algorithm.

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