Variants of the flower pollination algorithm for inversion of schlumberger sounding curve

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Abstract. Flower pollination algorithm (FPA) is a nature-inspired algorithm that mimics flowering plant pollination behavior. Yang created the FPA in 2012, and it has since proven to be superior to other metaheuristic algorithms. Many FPA variants have recently been developed through modification and hybridization. This paper provides FPA variants consisting of Modified Flower Pollination Algorithm (MFPA), elitism Flower Pollination Algorithm (eFPA), Dimension by Dimension Improvement Flower Pollination Algorithm (DDIFPA) and Flower Pollination Algorithm with Bee Pollinator (BPFPA). Validation of the code that has been created is done through simple model testing. All algorithms provide inversion results that are consistent with true value. The results of two synthetic models indicate that eFPA is the only algorithm that can reach the global optimum. Besides having the best level of accuracy, eFPA also has the best stability.

1. Introduction

To solve geophysical inverse problems, many inversion algorithms have been developed; like the Occam algorithm [1], Genetic Algorithm and Particle Swarm Optimization [2], and Lavenberg-Marquard using SVD [3]. Geophysical inverse issues are usually always ill-posed, meaning that no single solution can be found. This ill-posedness stems from the following typical issues related to geophysical data collecting: intrinsic non-uniqueness (primarily troublesome when employing potential approaches), data collection mistakes, prospective data set inconsistencies, and, most crucially, a lack of data. Even with the most exact data sets (no noise or systematic errors), only limited information about the subsurface can be gleaned, which is usually insufficient for resolving the inverse problem's non-uniqueness.

FPA is one of the newest algorithms. This algorithm is inspired by the process of pollinating flowers. According to [4], FPA is powerful than Genetic Algorithm and Particle Swarm Optimization in simulations. For self-potential data, [5] used FPA in geophysical inversion problems. As a result, FPA is reliable for interpreting SP data and this method does not need an initial model from anomalous sources. [6] proposed a dimension by dimension improvement based on FPA. As a result, this approach commit increase the convergence agility and the aspect of the result effectively. [7] proposed a BPFFA, compared to DE, PSO, FPA and K-Means, BPFFA is not only more accurate but also more stable. [8] popularized an embellished variant of FPA called MFPA. This algorithm is a hybridization of FPA with Clonal Selection Algorithm (CSA). The optimization results show that MFPA is more accurate than SA, GA, FPA, bat algorithm and firefly algorithm. [9] show that adding elitism is better than adding mutation.
operators and local search components to FPA. eFPA outperforms other strategies in many cases. In the event that the eFPA falls to construct optimal solution, the solution are compose within fair value.

2. Methods

2.1. Variants of the FPA

| a | b | c | d |
|---|---|---|---|
| 1. Establish a switch probability; | (a) | 1. Establish a switch probability $p \in [0,1]$; | (b) |
| 2. Begin the randomly generated population; | | 2. Make counter vector = zeros(1,npop); | |
| 3. Determine the pollen’s objective function; | | 3. define limit; | |
| 4. Identify best solution from the first population; | | 4. Begin the randomly generated population; | |
| 5. while absolute (minuses-maxuses) > 10^-10 & minuses > 10^-10; | | 5. Determine the pollen’s objective function; | |
| 6. if rand < p; | | 6. Identify best solution from the firs population; | |
| 7. for i=1 : n (n indicates total of pollen); | | 7. while absolute (minuses-maxuses) > 10^-10 & minuses > 10^-10; | |
| 8. select n best solution from pop to make clonespop | | 8. for i=1 : n (n indicates total of pollen); | |
| 9. do local pollination; | | 9. if rand < p; | |
| 10. end for | | 10. global pollination; | |
| 11. continue to make newpop; | | 11. if counter (1,i) == limit; | |
| 12. Find the current best solution gbest; | | 12. make new solution use simplex method; | |
| 13. if gbest not change for 100 iterations, hold gbest | | 13. counter (1,i)=0; | |
| 14. and replace pop with random generation | | 14. endif | |
| 15. end if | | 15. else | |
| 16. end for | | 16. do local pollination use EBMO; | |
| 17. identify best solution in the clonespop to | | 17. do crossover operation; | |
| 18. pop; | | 18. end if | |
| 19. Find the current best solution gbest; | | 19. if new solution better; | |
| 20. if gbest not change for 100 iterations, hold gbest | | 20. counter (1,i)=0; | |
| 21. and replace pop with random generation | | 21. else counter (1,i)=counter(1,i)+1; | |
| 22. end while | | 22. end for | |

**Figure 1.** FPA’s pseudo-code variants: a) MFPA, b) BPFPA, c) eFPA, d) DDIFPA.

2.2. Forward Modeling Formulation

[10] devised the following formula:

$$
\rho_d(s) = s^2 \int_0^\infty T(\lambda) J_1(\lambda s) \lambda d\lambda
$$

(1)

In this equation, $s$ represents the half-spaced electrode, $J_1$ represents the first-order Bessel function, and $\lambda$ represents the integral variable. $T(\lambda)$, the resistivity transform function, is denoted in such a way:
\[
T_i(\lambda) = \frac{T_{i+1}(\lambda) + \rho_i \tanh(\lambda h_i)}{1 + T_{i+1}(\lambda) \tanh(\lambda h_i / \rho_i)}, \quad i = n-1, \ldots, 1
\]  

(2)

\(n\) denotes the total of layers, \(\rho_i\) and \(h_i\) are the actual resistivity and thickness of the \(r^{th}\) layer.

2.3. Objective function

In general, appropriateness of model response to observed data instated by an objective function that must be minimized. The search for the smallest objective function is linked to the examination for the best model. The model is tweaked so that the model response matches the data. Throughout operation, it becomes fair that inverse modelling commit only be accomplished if the relationship between the data and the model parameters is accepted. The objective function:

\[
E = \sum_{i=1}^{N} (r_{hoi}^{cat} - r_{hoi})^2
\]

(3)

The objective function commit be defined as the root mean square error (ERMS) with coming equation to have a fairer connotation in equal unit as data (\(\Omega m\)):

\[
E_{RMS} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (r_{hoi}^{cat} - r_{hoi})^2}
\]

(4)

3. Results

3.1 Synthetic model

Validation of the code that has been created is done through simple model testing. The simple models used are homogeneous models, and two-layer models. All algorithms provide inversion results that match the true value.

| Parameters | True Value | Search Space | MFPA Min | MFPA Max | eFPA Min | eFPA Max | DDIFPA Min | DDIFPA Max | BPFPA Min | BPFPA Max |
|------------|------------|--------------|----------|----------|----------|----------|------------|------------|------------|------------|
| \(\Omega m\) | 200 | 12.61 | 500 | 200 | 200 | 200 | 200 |
| Two-layered Model | | | | | | | |
| \(\Omega m\) | 50 | 3,153 | 300 | 50 | 50 | 50 | 50 |
| \(\Omega m\) | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| \(h_1\) (m) | 14 | 0.5 | 20 | 14 | 14 | 14 | 14 |

The appropriateness of present algorithm was tested on synthetic models K-curve (three-layered model with \(\rho_1 < \rho_2 > \rho_3\)) and HK-type (four-layered model with \(\rho_1 > \rho_2 < \rho_3 > \rho_4\) curve. K-type curve uses a maximum iteration of 5000. While HK-type curve uses a maximum iteration of 7000. The results of the FPA variants are contrasted with the standard FPA. We used the same inverted parameters. Table 2 shows the search space as well as the experimental results. The inversion result value which is the same as the true value and the smallest standard deviation shows that eFPA has the best accuracy and stability.

| Parameter | True Value | Search Space | FPA Min | FPA Max | MFPA Min | MFPA Max | eFPA Min | eFPA Max | DDIFPA Min | DDIFPA Max | BPFPA Min | BPFPA Max |
|------------|------------|--------------|----------|----------|----------|----------|----------|----------|------------|------------|------------|------------|
| \(\Omega m\) | 100 | 31.53 | 2804 | 99.99 | 100 | 100 | 99.99 | 100 |
| \(\Omega m\) | 2000 | 9739 | 9739 | 1763.52 | 2037.67 | 2000 | 807.84 | 2009.44 |
| \(\Omega m\) | 3000 | 3299.99 | 3299.99 | 299.99 | 300 | 300 | 299.99 | 300 |
Each algorithms run 20 times (10 runs for each model), as illustrated in Figure 2. The eFPA reached the global optimum 11 times out of 20 runs. The FPA, MFPA, DDIFPA, and BPFPA failed in reaching the global optimum in the 20 runs.

![Figure 2. number of found global optimum](image)

![Figure 3. RMS error behavior comparisons](image)
Figure 3 reveal that eFPA has better performances than the MFPA, DDIFPA, BPFPA, and FPA in terms of the better RMS error. In Figure 3, it can be seen that eFPA can continue to explore when other algorithms stop at the local optimum (fixed RMS value throughout iterations). In addition to better exploration capabilities, eFPA also has better exploitation capabilities as well. It can be seen from the steep RMS eFPA curve. In contrast to DDIFPA, which has a very gentle RMS curve.

3.2. Field data

![Figure 4](image.png)

Figure 4. A field data set; (a) inversion results obtained with the FPA and IPI2Win. (b) The borehole data is also shown.

When it comes to field data, the eFPA is pitted against the standard FPA and IPI2Win. Figure 4 depicts the inverse solution of the eFPA for the observed data. The RMS error is 1.9 \( \Omega \text{m} \) (FPA and eFPA) and 2.56 m (FPA and eFPA) (IPI2Win). The inverse result from the FPA, eFPA, and IPI2Win are shown in Figure 4a. The inverse solution is generally consistent with the results collected applying FPA, IPI2Win, and the borehole data. At depths ranging from 0 to 2.18 m, the first layer has a resistivity value 27.81 \( \Omega \text{m} \). At depths ranging from 2.18 to 10.4 m, the second layer is a low resistivity layer (15.37 \( \Omega \text{m} \)). According to andesite breccia, the third layer has a higher apparent resistivity of 36.21 \( \Omega \text{m} \). (igneous rock has higher resistivity than clay at first and second layer).

4. Conclusions

The results of two synthetic models indicate that eFPA is the one and only algorithm that can reach the global optimum. Besides having the best level of accuracy, eFPA also has the best stability. Meanwhile, DDIFPA has poor performance, even worse than the FPA standard. In the case of field data, eFPA is better than IPI2Win based on RMS error. However, the eFPA has the same results as the FPA standard.

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