Memory Based Hybrid Dragonfly Algorithm (MHDA): a New Technique for Determining Model Parameter in Vertical Electrical Sounding (VES) Data

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Abstract. Vertical Electrical Sounding (VES) data inversion is a nonlinear inversion problem because several models can fit to the observed data. Therefore, a new approach based on nonlinear optimization technique is implemented which is called Memory based Hybrid Dragonfly Algorithm (MHDA). It is proposed to solve drawback of Dragonfly Algorithm (DA), i.e. low convergence rate which is caused by high exploration behaviour of DA. The drawback can lead to the local optimum solutions. MHDA successfully balances exploration and exploitation behaviours of DA to obtain global optimum solution. In this research, initially, MHDA is tested for the noise contaminated synthetic VES data to assess its performance. Subsequently, MHDA is applied for the field VES data. In both results, MHDA is able to provide Posterior Distribution Model (PDM) which is obtained from exploration process. All accepted models of PDM have lower misfit value than specified tolerance value in the inversion process. The PDM can be used to estimate solution via median value of PDM. Additionally, the uncertainty estimation of obtained solution can be determined from standard deviation value of PDM. The inversion results of synthetic and field VES data indicate that MHDA is an innovative technique to solve VES data inversion problem.

1. Introduction

Vertical Electrical Sounding (VES) is an active geophysical method which is one of the electrical surveying methods to investigate subsurface electrical structure as a depth function [1]. It utilizes direct current (dc) source which is induced through a pair of current electrodes into the ground and voltage difference is measured through a pair of potential electrodes [2]. VES is frequently applied for groundwater exploration [3], sediment thickness identification [1], dam leakage detection [4], and geothermal exploration [5]. Therefore, interpretation of VES data is very crucial because of its relevance for those cases. The interpretation of VES data is classified into three groups: linear filter theory, the widespread use of digital computers, and general linear inverse theory [5].

Linear inversion (local optimization) methods are the most popular approach to estimate subsurface resistivity structure from observation data [6]. However, VES data inversion is a nonlinear inversion problem which is ill-posed [7]. It means that several models can fit to the observed data which is known as non-uniqueness problem. Fernández-Álvarez et al. in [8] stated that global minimum in objective function topography lies on the bottom of a narrow, elongated valley with gradients close to null. Furthermore, global minimum is also surrounded by flat outer area with ridges which prevent search
agents to reach global minimum. Therefore, linear inversion methods are unable to obtain global minimum solution without any prior information (such as proper initial model) and it often converges to local minimum solutions. In order to solve that drawback, nonlinear inversion (global optimization) methods had been implemented by several researchers in VES data inversion: Particle Swarm Optimization (PSO) [7], Simulated Annealing (SA) [9], Genetic Algorithm (GA) [10], Dragonfly Algorithm (DA) [11], and Neighbourhood Algorithm (NA) [11].

In this research, a new approach based on global optimization technique is implemented to invert VES data which is called Memory based Hybrid Dragonfly Algorithm (MHDA). It was proposed by Ranjini and Murugan in [12] to solve the drawback of DA. Global optimization methods have two main behaviours: exploration and exploitation. Exploration enables the particle to explore specified search space and exploitation finds the best candidate as solution. If the algorithm is more explorative, the algorithm have low convergence rate. In other hand, the algorithm have rapid convergence rate if it is more exploitative. However, these two conditions often lead to local optimum solutions. Therefore, both behaviours must be balanced to obtain global optimum solution. MHDA successfully balances both behaviours of DA which is more exploitative. In order to assess its performance, initially, MHDA is tested for the noise contaminated synthetic data because it has not been applied yet in VES data inversion problem. Subsequently, MHDA is applied for field VES data in embankment stability investigation.

2. Methods
MHDA balances exploration and exploitation behaviours of DA by adding internal memory and iterative level hybridization into DA. DA is more exploitative because of Levy flight process. Additionally, it does not have internal memory which can lead the dragonflies toward previous possible solution [12]. The internal memory enables each dragonfly to consider previous obtained potential solutions. Further, it also enables dragonflies to consider overall best solution which is obtained by the swarm. These concepts are known as DA-pbest and DA-gbest which is similar to the concepts of PSO. Subsequently, the obtained internal memory is implemented for iterative level hybridization which executes DA and PSO in sequence. Therefore, there are two main schemes in MHDA: DA explores specified search space to obtain promising area and it provides internal memory, while PSO with internal memory exploits the area to obtain the best solution. These schemes will enhance exploitation capability of DA and will avoid the dragonflies toward local optimum solution.

In optimization process, a number of dragonflies and step vectors are initialized randomly in search space boundaries. Each dragonfly represents position vector in N-dimensional space, while step vector represents direction of a dragonfly in search space which is similar to the velocity vector of PSO. Then, fitness value of each dragonfly is calculated which represents optimality degree of a dragonfly. In DA scheme, internal memory is initialized which consists of DA-pbest and DA-gbest. DA-pbest is obtained by comparing fitness value of each dragonfly in current population with the best fitness in that iteration. Meanwhile, DA-gbest is obtained by comparing food fitness value in that iteration with previous iteration. In order to explore search space, step vector of each dragonfly is updated which is affected by five factors: separation, alignment, cohesion, attraction toward food, and distraction outward enemy. Furthermore, position of each dragonfly will be also updated which is based on previous position and updated step vector of dragonfly [13]. Subsequently, in PSO scheme, DA-pbest is assigned as initial particle and DA-gbest is assigned as gbest of PSO. In order to exploit the potential area, position (X) and velocity (V) vectors of particles in PSO are updated by modified equations:

\[ V_{k+1} = \omega V_k + c_1 r_1 (DA - pbest_k^i - X_k^i) + c_2 r_2 (DA - gbest_k^g - X_k^i) \]  
\[ X_{k+1} = X_k^i + V_{k+1}^i \]

where \( c_1 \) and \( c_2 \) are local and global acceleration constants, \( r_1 \) and \( r_2 \) are random numbers, \( DA - pbest_k^i \) is personal best of \( i \)-th particle, and \( DA - gbest_k^g \) is global best of the swarm in \( k \)-th iteration for PSO scheme. In this research, MHDA is applied to solve synthetic and field VES data inversion problem. Parameters of DA and PSO follow the research of Mirjalili in [13] and Marini and Walczak [14].
respectively. In optimization process, MHDA minimizes objective function (misfit) between observed and calculated VES data which is defined by [11]:

\[ L_1 \text{ Norm Misfit} = \left( \frac{\sum_{i=1}^{N} (d_{i}^{\text{obs}} - d_{i}^{\text{cal}})^2}{N} \right) \]

where \(d_{i}^{\text{obs}}\) is \(i\)-th observed apparent resistivity data, \(d_{i}^{\text{cal}}\) is \(i\)-th calculated apparent resistivity data, and \(N\) is total number of data observation. \(L_1\) norm is selected as objective function to be minimized because the obtained result is robust (insensitive) to outliers [15].

3. Results and Discussion

3.1. Inversion of synthetic VES data

Initially, MHDA is tested for noise contaminated synthetic VES data in order to assess its performance. 5 % Gaussian noise is introduced into synthetic data which represents field data. K-type earth model is used which is adopted from the research of Sharma in [9]. It is a three layers earth model which consists of resistive layer between conductive layers. It represents groundwater zone, mineralized zone, and saline water intrusion below resistive layer. It is a proper model to test the ability of MHDA because optimizers will be more difficult to converge toward global optimum solution. Moreover, DA is also applied to compare the obtained solution of MHDA. Synthetic VES data is generated by forward modelling process which is based on calculation of Sheriff in [16]. The result of forward modelling process is apparent resistivity curve as electrode space function which increases logarithmically in 1-1000 m range.

In optimization process, initially, search space boundaries of search agents are determined (Table 1). Number of particle and iteration are set: 100 particles, 300 iterations, and 200 hybridization iterations for MHDA, while 100 particles and 300 iterations are set for DA. In this research, the result of synthetic data inversion for both algorithms are determined by Posterior Distribution Model (PDM) which is obtained by exploration process in search space. In stochastic methods, search agents obtain several models which fit to the observed data. Therefore, they can provide PDM which contains possible solutions of an inversion problem. Furthermore, PDM is also used to estimate uncertainty boundaries of obtained solution in nonlinear inversion problem. All accepted models of PDM have lower misfit value than specified tolerance value which is determined by objective function in inversion process.

| Model Parameters | Search Space | True Model | Inverted MHDA | Inverted DA |
|------------------|--------------|------------|---------------|-------------|
| Thick1 (m)       | 10-80        | 50         | 51.4912 ± 0.1960 | 46.3133 ± 0.022 |
| Thick2 (m)       | 5-50         | 20         | 18.3950 ± 0.1302 | 13.0687 ± 0.003 |
| Res1 (ohm-m)     | 10-50        | 20         | 20.2532 ± 0.0734 | 19.7509 ± 0.005 |
| Res2 (ohm-m)     | 50-1000      | 500        | 526.3883 ± 3.626 | 507.889 ± 0.273 |
| Res3 (ohm-m)     | 10-100       | 50         | 48.6115 ± 0.2146 | 55.8316 ± 0.025 |
| Misfit           | 0.8135       |            | 0.995         |             |

Inversion result of synthetic VES data with MHDA is shown in Figure 1. Figure 1 (d) shows that misfit curve is relatively constant below 1. Therefore, this value is set as tolerance value. All accepted models as PDM are shown in Figure 1 (a). Solutions and model uncertainties can be estimated by median and standard deviation value of PDM respectively (Table 1). Figure 1 (a) shows that the solutions of each model parameter (blue cross) are sufficiently close to the true model (red dot). Additionally, each PDM exhibits the Gaussian distribution which means that uncertainty of obtained solution is low. Furthermore, the highest frequencies of histogram are also close to true model which can indicate solution of VES data inversion. Figure 1 (b) shows a good fitting curve between observed and calculated VES data. This fitting curve is also supported by calculated earth model which is close to true earth model (Figure 1 (c)). In Table 1, Misfit value of obtained solution shows that the inversion result of
MHDA is better than DA. It proves that MHDA successfully balances exploration and exploitation behaviours of DA. Therefore, MHDA can be applied to solve field VES data inversion problem.

![Figure 1](image_url)

**Figure 1.** (a) Histogram of PDM for each model parameter, (b) fitting curve between observed and calculated VES data, (c) comparison of true and calculated earth model, and (d) misfit curve as iteration function for inversion of synthetic data with MHDA.

### 3.2. Inversion of field VES data

In order to minimize the impact of Sidoarjo mud eruption, an embankment was built around it which is called LUSI (Lumpur Sidoarjo) embankment [17]. The LUSI embankment is an earth-fill dams which is composed by clay and silt soils. This condition can lead to embankment failures such as hydraulic failure, seepage failure, and structural failure [17] which cause embankment collapse. VES method was applied to investigate the LUSI embankment stability at point 83 (P. 83). In order to invert VES data of LUSI embankment, search space boundaries are set (Table 2) which is four layers earth model. Then, number of particle and iteration are set: 100 particles, 300 iterations, and 300 hybridization iterations for inversion process. Inversion result of LUSI embankment VES data is shown in Table 2.

| Model Parameters | Search Space | Inverted Model |
|------------------|--------------|----------------|
| Thick1 (m)       | 1-20         | 1.000 ± 0.00   |
| Thick2 (m)       | 1-20         | 1.059 ± 0.040  |
| Thick3 (m)       | 1-20         | 5.043 ± 0.1544 |
| Res1 (ohm-m)     | 15-40        | 28.696 ± 0.047 |
| Res2 (ohm-m)     | 15-40        | 15.000 ± 0.208 |
| Res3 (ohm-m)     | 0.5-15       | 8.832 ± 0.0103 |
Res4 (ohm-m) & 0.5-15 & 0.526 ± 0.0308 & Misfit & 0.5319

Figure 2 (d) shows that misfit curve is relatively constant below 0.7, therefore it is set as tolerance value. All accepted model with lower misfit value than tolerance value is shown in Figure 2 (a). The inversion result (Table 2) has good fitting curve between observed and calculated data (Figure 2 (b)). Further, uncertainty of obtained models is low. Inversion result (Figure 2 (c)) indicates that resistivity value of LUSI embankment at P. 83 decreases as a depth function. It is caused by fluid saturation through LUSI embankment cracks which decreases embankment stability. This result is also supported by research of Sungkono et al. in [18]. Therefore, LUSI embankment at P. 83 has a large potential for collapse.

**Figure 2.** (a) Histogram of PDM for each model parameter, (b) fitting curve between observed and calculated VES data, (c) comparison of true and calculated earth model, and (d) misfit curve as iteration function for inversion of LUSI embankment VES data.

**Conclusion**

MHDA, a new global optimization technique, has been implemented to solve VES data inversion problem which is highly non-linear inversion problem. In synthetic and field VES data inversion, solution and uncertainty of obtained solution can be estimated by PDM which obtains from exploration behaviour of MHDA. In noise contaminated synthetic VES data inversion, the obtained solutions are close to the true model. Furthermore, the uncertainty of obtained models are low which indicate robustness of MHDA. In field VES data Inversion, the result indicates that LUSI embankment at P. 83 is saturated by fluid. It is shown by resistivity value of LUSI embankment at P. 83 decreases as depth...
function. Therefore, LUSI embankment at P. 83 has potential for collapse. In both inversion results, MHDA is an innovative technique to solve VES data inversion problem.

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