Defect reconstruction of magnetic flux leakage measurements based on single dimension PSO algorithm

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Abstract. Magnetic flux leakage (MFL) detection is widely used in the technology of oil and gas pipeline intelligent detection at present. For the defect reconstruction problem in MFL detection, a new improved particle swarm optimization (PSO) algorithm, called SDPSO, is introduced to enhance the accuracy of defect profile reconstruction in this paper. In order to reduce the interaction between multidimensional information, dimensional coupling will deteriorate the search speed and convergence accuracy of the algorithm, a single dimension evolution strategy is complemented to optimize the tradition PSO algorithm. Each generation of evolution only updates a single dimension of the objective function. The dimension with the maximum error between the candidate signal and reference signal is selected as the one which need to be updated in next generation. In order to testify the performance of the proposed method, the simulated signals are utilized to compare with PSO algorithm. The experiment results verify that the proposed method has a higher adequacy of the performance in terms the quality of the solution and robustness for noise.

1. Introduction
Petroleum and natural gas, as important industrial materials, play a crucial part in the national economy and industry development [1]. A vast network of pipelines has been widespread transportation equipment in most countries for oil and natural gas for a long time [2-5]. Since extensive networks of pipelines are normally buried underground, it is inevitable to be damaged by corrosion, internal stress, welding, slag inclusion, and other factors [6]. The potential risk of the pipeline leakage increases significantly with the time extension of the pipeline in service. Therefore, it is great significance to periodically inspect and analyze in structures and specimens for the ferromagnetic pipelines. The objective of MFL inspection is to reconstruct the profiles of the defects in the pipelines and find the defects in advance before the occurrence of the leakage. Therefore, early detection of the pipe faults according to the result of magnetic flux leakage (MFL) inspection may avoid severe collapses that involve environmental damage and high costs.

At present, the inversion method of defect information estimation can be summarized into two categories: direct method and iterative method. On the basis of the forward problem, the iterative method solves the reverse problem by means of the feedback. Based on the initial appearance of the defect, the predicted MFL signal is obtained by the forward problem, and the defect signal is constantly modified to reduce the error between the predicted MFL signal and the preference signal. The defect reconstruction problem composed of many uniform discrete values is often taken regard as a nonlinear
high-dimension optimization problem to solve. The framework of defect profile reconstruction based on the iterative inversion process is shown in Fig. 1.

From Fig. 1, it can be seen that the update strategy of defect profile is essential component of the defect reconstruction frame. The forward model predicts the magnetic response of ferromagnetic materials. The update of the defect profile aims to provide the high quality candidate predict profiles, which are solved by formulating as an optimization problem. Many optimization approaches have been used to correct the defect profile iteratively. It is generally accepted that PSO is an efficient and effective optimization technique and has been applied to deal with various engineering applications such as signal and image processing. However, with the popularization of the application of PSO, it has some insufficient ability, such as weak local search ability, slower convergence speed and low convergence accuracy. In order to overcome the disadvantages of the algorithm and improve the local search ability, the main characteristic of our proposed algorithm is that single dimension evolution strategy to optimize the initial PSO algorithm and improve the convergence speed.

2. The PSO Algorithm with single dimension

2.1. PSO

Particle Swarm Optimization (PSO) was first proposed by Eberhart and Kennedy in 1995. Its basic concept originates from the study on the foraging behavior of birds. Each particle can be regarded as a searching individual in the n-dimensional search space. The current position of the particle is a candidate solution of the corresponding optimization problem, and the flight of the particle is regarded as searching process of the individual. The velocity of the particle can be adjusted dynamically according to the historical optimal position of the particle and the historical optimal position of the population. The velocity update formula of particle swarm optimization algorithm is as follows[7]:

$$v_{id} = \omega v_{id} + c_1 r_1 (p_{best} - x_{id}) + c_2 r_2 (g_{best} - x_{id})$$  (1)

where $c_1$ and $c_2$ are learning factors; $r_1$ and $r_2$ are random numbers in (0,1); $p_{best}$ is the currently found best solution of each particle; $g_{best}$ is the best solution which is found from the entire population. The position update formula of particle swarm optimization algorithm is as follows:

$$x_{id} = x_{id} + v_{id}$$  (2)

2.2. The PSO algorithm with single dimension

In order to avoid the mutual interference between multidimensional information, according to the comparison between the best signal in swarm and the reference signal, the dimension with the largest error from the whole solution is selected as the evolution center. The selection of the dimension can be derived from the following equation,

$$d_0' = \arg\max_i (RP_i - PP_{gi})$$  (3)
\[ d^i = N(d^i_0, s) \]  
where \( d^i \) is the \( i \)-th component of the reference signal, \( d^i_0 \) is the \( i \)-th dimension of the global best nest at \( t \) iteration. \( N(d^i_0, s) \) is Gaussian distribution with mean \( d^i_0 \) and standard deviation \( s \).

Equilibrium evaluation of single evolution strategy is updated every generation evolution, only update the dimension with the maximum error between the reference single and the MFL single of candidate defect, so the algorithm can ensure that the search direction during the process of optimization algorithm of adjustment, and does not affect the efficiency of the algorithm.

3. Inversing approach based on SDPSO

Each particle in SDPSO algorithm represents a defect profile, and the forward model based on RBFNN (radial basis function neural network) is used to generate MFL signal. The algorithm is implemented using the following steps in detail:

Step 1: Initialize the particles of the SDPSO algorithm and set all the parameters, e.g. the number of particles \( N \), the maximum iteration of \( T_{\text{max}} \), inertia weight \( \omega \), acceleration coefficients \( c_1 \) and \( c_2 \). \( N \) particles of SDPSO algorithm represent the predicted profiles as follows:

\[
\begin{bmatrix}
PP_{p1} & PP_{p2} & \cdots & PP_{pd} \\
PP_{p1} & PP_{p2} & \cdots & PP_{pd} \\
\vdots & \vdots & \ddots & \vdots \\
PP_{pN} & PP_{pN} & \cdots & PP_{pd}
\end{bmatrix}
\]  

(5)

Step 2: Obtain the MFL signal of the corresponding particles by the RBFNN.

Step 3: Calculate the fitness value of each particle according to the given preference profile. The best nest is selected by the fitness value.

\[
f = \frac{1}{2} \sum_{i=1}^{n} (PP_i - \widehat{PP}_i)^2
\]  

(6)

Step 4: Generate the new particles by SDPSO algorithm.

Step 5: Determine whether the maximum number of the iterations is met. If \( t \leq T_{\text{max}} \), turn to Step 2. Otherwise, output the final predicted defect profile.

4. The simulation experiment results

To test the performance of the proposed approach, some defects were reconstructed in the experiment. The MFL data simulated was generated by ANSYS 15.0. The defect signals including 360 2-D rectangle samples were used to produce the corresponding MFL signals. The data were divided into two groups. The first part containing the 230 date was mainly used to train by RBFNN, and the second part was used to test the reconstruct result of the proposed inversing approach. The number of samples of a defect profile was 50. Four defect profiles listed in Table 1 were chosen as the test defect profiles, The MFL measurements with an SNR of 20 and 10 dB noise. The parameters of PSO algorithm were given in Table 2.

The reconstruction result of defect profile is shown in Table 3 and Fig.2. In Fig.2, the true profile is described by the blue line, and the predicted defect profile is represented by the pink line. It is noted that the average results in the tests of 30 turns is indicated in Table 3. PSD and PDE are the indicators to evaluate the performance of the methods.

\[
PSD = \sqrt{\frac{1}{N_{\text{DOF}}} \sum_{i=1}^{N_{\text{DOF}}} (RP_i - PP_i)^2}
\]  

(7)

\[
PDE = \left| \min(RP) - \min(PP) \right|
\]  

(8)

For PSO and SDPSO, it is clearly visible the preference of SDPSO is better than PSO, this result demonstrates that the proposed inversing approach based on SDPSO is effective.
Table 1  Four defect profiles

| Sample index | Width | Depth |
|--------------|-------|-------|
| 1            | 30    | 2.80  |
| 2            | 25    | 1.60  |
| 3            | 15    | 4.08  |
| 4            | 35    | 6.72  |

Table 2  Parameters of PSO algorithm

| Parameter          | Value |
|--------------------|-------|
| Population size    | 100   |
| $\omega$           | 0.73  |
| $c_1$              | 1.5   |
| $c_2$              | 1.5   |

(a) Defect profile and estimated profiles (sample No. 1)

(b) Defect profile and estimated profiles (sample No.2)
5. Conclusion
In this paper, we have proposed a novel defect profile reconstruction approach based on improved PSO. In the proposed approach, the MFL signal is used to perform as a reference to estimate the equality of the predicted defect profiles in the inverting process. To improve the accuracy of defect profile reconstruction approach based on PSO algorithm, single dimension evolution strategy is introduced to enhance the quality of the solution in the search process. The proposed PSO algorithm is tested by both the simulation. In order to prove the ability of the reconstruction in noise circumstance, the proposed approach can reconstruct the defect profile by adding noise in preference MFL signal. The compared results indicate that SDPSO can achieve higher accuracy.

### Table 3 Performance comparison of the algorithms

| Sample index | PSD  | SDPSO | PDE  | SDPSO |
|--------------|------|-------|------|-------|
|              | PSO  | SDPSO | PSO  | SDPSO |
| 1            | 0.1737 | 0.1085 | 1.5497 | 0.8586 |
| 2            | 0.1607 | 0.0945 | 1.5228 | 0.8342 |
| 3            | 0.1669 | 0.1184 | 1.5732 | 1.0832 |
| 4            | 0.2106 | 0.1356 | 1.2381 | 0.9622 |
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