**Image Reconstruction Using Particle Swarm Optimization (PSO) in Electrical Impedance Tomography**

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**Abstract**— Electrical impedance tomography (EIT) aims in reconstructing resistivity distribution of inhomogeneous objects, by using the voltage measurements from the boundary electrodes and facilitates in solving non linear inverse problems. For the medical imaging research community, developing a suitable reconstruction algorithm is a challenging task as the inverse problem in EIT is severely ill-posed. This paper proposes a heuristic particle swarm optimization (PSO) method for solving the static EIT inverse problems. Experiments are performed using 64 finite elements mesh by varying the swarm size, and the reconstruction performances are evaluated in terms of the fidelity measure such as mean relative error (MRE) which indicates the error between the estimated and true values of resistivity. It is observed from the simulation results that the optimization is attained for the swarm size of 28 for which the reconstruction error is minimum. Further the spatial resolution is improved in larger extent compared to that of modified Newton – Raphson method at the outright of relatively expensive computational time.

Keywords— particle swarm optimization (PSO), electrical impedance tomography (EIT), inverse problem.

**I. INTRODUCTION**

Electrical impedance tomography (EIT) is a functional non-invasive imaging technique in which image of the part of the body is inferred through impedance measurements [1–5]. Through the injection of low frequency currents between pair of electrodes attached to skin of the subject, a resistivity map is obtained and the potential difference between all other electrodes are measured to reconstruct the impedance distribution. In the recent years, EIT imaging procedure has gained its importance for clinical diagnosis due to its non-invasive procedure for imaging pulmonary ventilation, gastric emptying and brain function [1–5]. The principle of EIT is based on the back image reconstruction, which is highly ill-posed inverse problem [6]. In general, as it is necessary to calculate the internal conductivity map from the measurements made on the surface of the object and the resultant measured potentials, EIT image reconstruction is a non-linear function of conductivity [1–2,5–7].

For EIT imaging studies, it is a general procedure to create a finite mesh with inhomogeneous conductivity distribution. Then the forward problem is used to calculate the peripheral potentials for the conductivity distribution, termed as measured potentials $V_{\text{mesd}}(1…M)$, where $M$ is the number of measurements. Now the task of EIT is to successfully simulate a mesh, which can yield boundary potentials, termed as simulated potentials $V_{\text{sim}}(1…M)$, with values closer to the measured potentials. The performance of an inverse algorithm is evaluated on the basis of how successfully EIT can generate, update and yield a simulated mesh closer to the inhomogeneous mesh. In other words, it is simply a problem of minimizing the difference between the simulated and measured potentials. Thus, as shown in 1, the EIT inverse problem can be represented as an optimization problem of minimizing the objective function $f(\sigma)$, where $\sigma$ is the resistivity distribution vector in the object, $V_{\text{mesd}}$ is the vector of measured potentials on the boundary, and $V_{\text{sim}}$ is the vector of computed peripheral voltages respect to $\sigma$, which can be obtained using finite element method (FEM) [8,9].

$$f(\sigma) = \frac{1}{2} \left( |V_{\text{sim}} - V_{\text{mesd}}|^T |V_{\text{sim}} - V_{\text{mesd}}| \right)$$

![Fig. 1 Schematic of EIT inverse problem as an optimization problem](image)

EIT inverse problem is considered as the two dimensional image reconstruction of specific medical imaging where
several stochastic and deterministic approaches have been reported in the literature [8-10].

Few authors have attempted evolutionary algorithms and other optimization techniques to solve the EIT inverse problems [8-10]. R. Olmi et al.,[8] has applied genetic algorithm to the square and circular region meshes, with the assumed homogenous conductivity of 1 S/m and respective internal sub region conductivities of 3 S/m, and 5 S/m. Combinational methods of traditional modified Newton- Raphson (MNR) method with differential evolution (DE) [9] and Simulated Annealing (SA) [10] for different mesh sizes have been reported in the literature.

These works reveal that stochastic techniques can be used as a promising tool for solving EIT problems. Hence the scope for identifying better technique to minimize the objective function thereby achieving better optimization is still open.

This paper proposes a particle swarm optimization (PSO) technique for providing solution for EIT inverse problem. The main motivation behind this approach is due to its robustness in solving continuous non-linear problem and generation of superior solutions with less computational time and more stable convergence characteristics than other stochastic methods performance [13-14, 19-22].

II. PARTICLE SWARM OPTIMIZATION (PSO)

Particle swarm optimization (PSO) is a population based stochastic optimization technique originally developed by the inspiration from the social collective behavior of birds interacting with each other and their environment [13]. It is an optimization tool that provides a population-based search procedure in which individuals called particles change their positions (states) with respect to time [14]. Considering a multidimensional search space, each particle changes its position based on self experience, and the experience of neighboring particles, making use of the best position (pbest) encountered by itself and its neighbors (gbest), during flight [14]. The swarm direction of a particle is defined by the set of particles neighboring the particle and its past experience. Each particle tries to modify its position based on current positions, current velocities, the distance between the current position and pbest, the distance between the current position and the gbest, which can be modeled mathematically as, [14],

\[
v_{i}(t+1) = w v_{i}(t) + c_{1} \cdot \text{rand()} \cdot (p_{\text{best}_{i}} - x_{i}(t)) + c_{2} \cdot \text{Rand()} \cdot (g_{\text{best}} - x_{i}(t)).
\]

\[
x_{i}(t+1) = x_{i}(t) + v_{i}(t+1).
\]

Where,
- \(n\) number of particles in a group;
- \(m\) dimension of the problem;
- \(t\) iteration counter;
- \(w\) inertia weight factor;
- \(c_{1}, c_{2}\) acceleration constant;
- \(\text{rand()}, \text{Rand()}\) uniform random values

III. THE PSO APPROACH TO EIT

The first step in solving EIT inverse problem using PSO is to generate a set of random tentative solutions (particles). The swarm size (S) is equivalent to population size which determines the number of swarms required. In PSO-EIT, \(N\) is assigned as the value for the dimension of the problem ‘m’, where \(N\) is the number of elements used for constructing the finite element mesh. Fig.2 depicts the flowchart for finding the solutions to EIT inverse problems using PSO –EIT algorithm.

Fig.2 Flowchart describing the PSO based optimization procedure
IV. MESH SIMULATION

The Finite element mesh used in this work is created using EIDORS, ‘a2c’ two dimensional common model, which has 64 elements [11-12], designated as X. As shown in Fig.3, inhomogeneous conductivity value of 3 S/m is assigned to elements X (1... 8), whereas all other elements X (9...64) has the value of 1 S/m.

\[ X(1...8) \sim 3 \text{ S/m}, \]
\[ X(9...64) \sim 1 \text{ S/m} \]

![Fig.3 EIT simulations example FEM of 64 elements used for testing reconstruction performance](image)

The EIT forward problem is solved for this inhomogeneous model and the peripheral potentials computed are considered as measured potentials. It is assumed that there are 16 electrodes placed on the boundary, and neighboring method is used in data collection with 16 different configurations, for a total of 208 measurements. The image reconstruction for this model using PSO-EIT is executed based on the following steps:

1. Assign the values for the swarm size (S), number of mesh elements (N), minimum and maximum values of conductivity distribution \( \sigma_{\text{min}} \) and \( \sigma_{\text{max}} \), maximum number of iterations and the maximum velocity step \( v_{\text{max}} \). For our model \( \sigma_{\text{min}} = 1 \text{ S/m and } \sigma_{\text{max}} = 3 \text{ S/m.} \)

2. Initialize the swarm of size with random values within the constraints \( \sigma_{\text{min}} \) and \( \sigma_{\text{max}} \).

3. Now each particle or each row of swarm has 64 random conductivity values within the constraints.

4. Solve EIT forward problem for each row and compute the corresponding simulated potentials. The number of measurements of simulated potentials will be equal that of measured potentials (208 measurements in this case).

5. Evaluate the fitness function and calculate the pbest and gbest by running all particles and iterations as per the procedure explained before.

V. RESULTS AND DISCUSSION

In the simulations using EIT-PSO, we choose, \( c_1 = c_2 = 2 \), initial and end value of \( w \) as 1 and 0.4 respectively [14]. The number of iteration is chosen as 2500 which yields a best tradeoff between the reconstruction error and computational time. To evaluate the quality of reconstruction results, fidelity measure, such as mean relative error (MRE) is used, which is defined as,

\[ \text{MRE} = \frac{\sum_{i=1}^{N} | \sigma_i^{\text{computed}} - \sigma_i^{\text{true}} |}{\sum_{i=1}^{N} \sigma_i^{\text{true}}} \]  

(4)

For our experimentation, various Swarm sizes from 4 to 32 are considered and 10 trials are carried out. The reconstruction results are shown in TABLE1, in which the values of average MRE and time taken to perform the simulation on the personal computer Intel Core2 CPU 4300, 1.8 GHZ, and 2 GB RAM are tabulated.

<table>
<thead>
<tr>
<th>Swarm size</th>
<th>Average MRE</th>
<th>Average time (secs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>0.070792219</td>
<td>1081</td>
</tr>
<tr>
<td>8</td>
<td>0.000623764</td>
<td>2586</td>
</tr>
<tr>
<td>16</td>
<td>2.66 X 10^{-5}</td>
<td>3528</td>
</tr>
<tr>
<td>20</td>
<td>1.98 X 10^{-8}</td>
<td>5941</td>
</tr>
<tr>
<td>24</td>
<td>8.76 X 10^{-10}</td>
<td>7039</td>
</tr>
<tr>
<td>28</td>
<td>2.52 X 10^{-11}</td>
<td>8546</td>
</tr>
<tr>
<td>32</td>
<td>3.15 X 10^{-7}</td>
<td>9983</td>
</tr>
</tbody>
</table>

From the results it is observed that the error at a given iteration generally decreases when the swarm size is increased from 4 to 28. But the error does not linearly decrease with the iterations or the swarm size because of the inherent nature of the PSO. From the existing works reported in the literature [8-10], it is understood that exact comparison cannot be performed with this proposed scheme, as the results reported are based on different experimental datasets.

![Fig. 4. PSO-EIT image reconstruction for swarm size of 28](image)
Fig. 5. MNR based image reconstruction

As shown in Fig. 4, geographically similar mesh shapes closer to the inhomogeneous model of Fig. 3, are observed using swarm sizes of 28. From Figs. 4 & 5, it can be demonstrated that PSO – EIT outperforms MNR in terms of spatial resolution.

V. CONCLUSION AND FUTURE WORK

This paper discusses the particle swarm optimization (PSO) technique for solving Electrical Impedance Tomography (EIT) inverse problem. Due to its stable convergence characteristics compared to other stochastic methods, the proposed technique reported in this study yields the conducting values closer to the actual values. Experimental results demonstrate that the swarm size of 28 found to be optimal in terms of minimizing the objective function. Further the image reconstruction using PSO-EIT found to be better than modified Newton-Raphson (MNR) method. It can be revealed from the earlier reports that the genetic algorithm and differential evolution based optimization techniques suffer from premature convergence that degrades its performance in terms of optimizing highly epistatic objective functions [14,18].

Selecting the FEM is crucial in image reconstruction as it is different for different objects of imaging. The present work has explored the possibility of using PSO for image reconstruction and the results are encouraging for the FEM considered.

In order to enhance less computational complexity for real-time applications, the current procedure found to be expensive. The PSO algorithm can be further extended to solve finer dense meshes under noisy environments.

Selection of right FEM and optimal swarm size suitable for the organ of imaging are the potential problems for further extensive research.

REFERENCES