Enhanced Artificial Immune System Algorithm Using PSO and GA Principles

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Objective and Motivation

**Objective:** Apply Enhanced Artificial Immune System (EAIS) algorithm to Electromagnetics applications

**Motivation:**

- Nature provides *heuristic* optimization methods that can be utilized in engineering applications.
- Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Artificial Immune System (AIS) are heuristic optimization methods.
- The EAIS inspired by local search ability of PSO and cross-over ability of GA.
Outline

• Principles of Heuristic Optimization Algorithms
  – Conventional Artificial Immune System (AIS)
  – Enhanced Artificial Immune System (EAIS)
• User Defined Parameter
• Performance Comparison
  – Mathematical test functions
  – EM application: Antireflective Surface Design
• Conclusions
The Principles of Heuristic Optimization Methods

Randomly distribute all agents
Calculate cost, $C_i$
Check for convergence
Heuristic Optimization Specifics

- Randomly sampling of the optimization space by “agents”
- Rely on random sampling of the optimization space by “agents” using collective intelligence.

C = 0
Stop

Principles
Parametric Analysis
Performance Comparison
Conclusions

C1
C2
C_max

Find peak of 2D sinc function space by “agents”
Basic Principle of Conventional AIS

1. Produce antibodies (Abs) that recognize antigens
2. Generate new random genetic modifications to antibodies via cloning and mutation to best suit antigen

Applications to Engineering:
- Antibodies represent possible solutions to the problem,
- The optimization space is translated to binary form to emulate gene behavior.

Block Diagram of Conventional AIS

- Randomly distribute all agents
- Calculate cost, $C_i$
- Check for convergence
- Heuristic Optimization Specifics
- Update distribution
- Conventional AIS Procedure:
  - Sort
  - Combine
  - Mutate, ($\rho_m$)
  - Clone, ($\rho_c$)
  - $N_c + N_\alpha$
  - $N_c$
  - $N_c$

Yes or No: Stop
Conventional AIS Procedure

Update population

Sort

Combine

Mutate

Clone

\[ \rho_{c1} > \rho_{c2} \]

\[ \rho_{m1} < \rho_{m2} \]

Initial Set (sorted)

\[ N_a \]

Top set \((N_\alpha)\)

\[ N_c \]

Cloned Set

\[ N_c \]

Mutate

Combine and sort

Combined Set

Principles

Parametric Analysis

Performance Comparison

Conclusions
Block Diagram of Enhanced AIS

Randomly distribute all agents

Calculate cost, $C_i$

Check for convergence

Heuristic Optimization Specifics

Yes

No

Stop

Update distribution

Enhanced AIS Procedure vs. Conventional AIS Procedure

- Conventional:
  - Sort
  - Combine
  - Cross-over $(\rho_x)$
  - Sort
  - Combine
  - Mutate, $(\alpha)$
  - Clone, $(\rho_c)$

- Enhanced:
  - Sort
  - Combine
  - Cross-over $(\rho_x)$
  - Sort
  - Combine
  - Mutate, $(\alpha)$
  - Clone, $(\rho_c)$

Principles | Parametric Analysis | Performance Comparison | Conclusions
Enhancement: (i) Mutation Stage

### Conventional AIS

- **Intelligence:** - Number of flipped bits.

- **Mechanism:**
  - Randomly distribute all agents
  - Bit position will be flipped randomly

### Enhanced AIS

- **Intelligence:** - Proposed a target oriented process
  - Inspired by velocity update mechanism of PSO

- **Mechanism:**
  - Define mutation rate $\alpha$
  - The new Ab is updated by $\rho_1 \times Ab + \alpha \times \rho_2 \times (Ab - Ab_{best})$

### Formulas

$$ V_{n+1} = W \times V_n + c_1 \rho_1 \times (\rho_{b_n} - x^{\alpha}) = \exp(-1/i) $$

where:
- $V_n$: Velocity of Ab
- $\rho_{b_n}$: Acceleration factor (personal)
- $x^{\alpha}$: Index of Ab
- $\rho_1$, $\rho_2$: Acceleration factor (global)

### Algorithm Steps

1. **Sort**
2. **Combine**
3. **Cross-over**
4. **Sort**
5. **Combine**
6. **Mutate, ($\alpha$)**
7. **Clone, ($\rho_c$)**
8. **Stop**

### Reference

Enhancement: (ii) Cross-over Stage

1. Randomly distribute all agents $(N_{\beta})$
2. Calculate cost, $C_i$
3. Split
4. Heuristic Optimization Specifics
5. Cross Over Set $N = \alpha \ast N_a$
6. Check for convergence
7. Yes
   - Stop
8. No
   - Combine and sort
   - Enhanced AIS procedure

Steps:
- Sort
- Combine
- Cross-over
- Sort
- Combine
- Mutate, $(\alpha)$
- Clone, $(\rho_c)$
Enhancement: (iii) Position Updated Stage

- Set 1: Group memory: Keep as they are
- Set 2: Local search: search around Ab best using PSO mechanism
  - Range of local search is changing dynamically, i.e. focusing more and more to Ab best
- Set 3: Global search: Randomly search over optimization space
Mathematical Test Functions

\[ f_{\text{Grie}}(x) = \frac{1}{4000} \sum_{i=1}^{N} x_i^2 - \prod_{i=1}^{N} \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1, -50 \leq x_i \leq 50. \]

Minimum value is 0

\[ f_{\text{Rast}}(x) = \sum_{i=1}^{N} (x_i^2 - 10\cos(2\pi x_i) + 10), -10 \leq x_i \leq 10. \]

(a) Griewank

(b) Rastrigin

\[ f_{\text{Rose}}(x) = \sum_{i=1}^{N} (100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2), -10 \leq x_i \leq 10. \]

(c) Rosenbrock
Choosing User Defined Parameters (1)

### General Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Antibodies ( N_a )</td>
<td>20</td>
</tr>
<tr>
<td>Number of bits ( N_b )</td>
<td>16</td>
</tr>
<tr>
<td>Maximum # Iteration ( N_{\text{max}} )</td>
<td>1000</td>
</tr>
</tbody>
</table>

### Parametric Study

<table>
<thead>
<tr>
<th></th>
<th>Conventional AIS</th>
<th>Enhanced AIS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cloning rate ( \rho_c )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mutation rate ( \rho_m )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cloning rate ( \rho_c )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cross-over rate ( \rho_x )</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

- Run 100 simulations for good statistical sample
Choosing User Defined Parameters (2)

### Parametric Study

<table>
<thead>
<tr>
<th>Conventional AIS</th>
<th>Enhanced AIS</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Cloning rate (increase $N_{\text{call}}$)</td>
<td>• Cloning rate (increase $N_{\text{call}}$)</td>
</tr>
<tr>
<td>• Mutation rate</td>
<td>• Cross-over rate (increase $N_{\text{call}}$)</td>
</tr>
</tbody>
</table>

**Measure of effectiveness $\propto^{-1} (\text{AvgBest}_{\text{Cost}} \cdot N_{\text{Call}})$**
Conventional AIS

Measure of effectiveness as a function of $\rho_c$ and $\rho_m$

(a) Griewank

(b) Rastrigin

(c) Rosenbrock

(d) Average of 3 functions

Choose $\rho_c = 0.3$, $\rho_m = 0.1$
Enhanced AIS

Measure of effectiveness as a function of $\rho_c$ and $\rho_x$

Choose $\rho_c = 0.5$, $\rho_x = 0.8$

- (a) Griewank
- (b) Rastrigin
- (c) Rosenbrock
- (d) Average of 3 functions
EAIS : Cross-over and Position Updated Effect

(a) Griewank

(b) Rastrigin

(b) Rosenbrock
Performance Comparison

Math functions

(a) Griewank

(b) Rastrigin

(b) Rosenbrock

Principles
Parametric Analysis
Performance Comparison
Conclusions
Express the periodic spatial variation in permittivity as a Fourier series expansion. Fields are represented as a summation of possible modes.

Antireflective Surface Design

Normal Incidence

Fix $d_1 = 0.1$ inches
$d_2 = 0.05$ inches

(32 – 38 GHz)

$\Gamma \leq -30$ dB

Reference: Broadband Antireflective Properties of Inverse Motheye Surfaces, Mark S. Mirotznik, Member, IEEE, Brandon Good, Student Member, IEEE, Paul Ransom, Member, IEEE, David Wikner and Joseph N. Mait, Senior Member, IEEE
Antireflective Surface Design: Optimization Parameters

<table>
<thead>
<tr>
<th>AIS Parameters</th>
<th>EAIS Parameters</th>
<th>PSO Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N_b$</td>
<td>$N_b$</td>
<td>Boundary condition</td>
</tr>
<tr>
<td>12</td>
<td>12</td>
<td></td>
</tr>
<tr>
<td>$\rho_c$ (clone rate)</td>
<td>$\rho_c$ (clone rate)</td>
<td>$C_1$ (local)</td>
</tr>
<tr>
<td>0.3</td>
<td>0.5</td>
<td></td>
</tr>
<tr>
<td>$\rho_m$ (mutate rate)</td>
<td>$\rho_x$ (cross over rate)</td>
<td>$C_2$ (global)</td>
</tr>
<tr>
<td>0.1</td>
<td>0.8</td>
<td></td>
</tr>
</tbody>
</table>

$N_{\text{call}}$: 70  
$N_{\text{max}}$: 100  
$\Gamma \leq -30\text{dB}$

Run 10 simulations for good statistical sample
Antireflective Surface Design: Solution

AR: Solution

<table>
<thead>
<tr>
<th></th>
<th>AIS</th>
<th>EAIS</th>
<th>PSO</th>
</tr>
</thead>
<tbody>
<tr>
<td>$h_1$ (mm)</td>
<td>1.378</td>
<td>1.383</td>
<td>1.374</td>
</tr>
<tr>
<td>$h_2$ (mm)</td>
<td>3.910</td>
<td>3.863</td>
<td>3.828</td>
</tr>
<tr>
<td>$\lambda$ (mm)</td>
<td>2.764</td>
<td>2.761</td>
<td>2.768</td>
</tr>
</tbody>
</table>

Reflection vs. Frequency

Fix $\lambda = 2.76$
Antireflective Surface Design: Performance Comparison

AR: Comparison AIS, EAIS, PSO

<table>
<thead>
<tr>
<th>AR-Design</th>
<th>AIS</th>
<th>EAIS</th>
<th>PSO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Success rate %</td>
<td>70</td>
<td>70</td>
<td>80</td>
</tr>
<tr>
<td>Avg Iter</td>
<td>53</td>
<td>30</td>
<td>48</td>
</tr>
</tbody>
</table>
Conclusions

- Enhanced AIS was inspired by principles of PSO and GA.
- A parametric study was carried out to understand the effects of different parameters of these algorithms.
- Position updated stage has major role in EAIS.
- Cross-over stage is suitable for challenging optimization problems that have many local optimum points.
- Performance of Enhanced AIS algorithm was compared with Conventional AIS and PSO in three math functions and also in EM application.
Thank you

Q&A
Combine and sort

Choose $N_a$.

Top Set $(N_\beta)$

Combined Set

$N_c + N_\alpha$

Split

Cross Over Set

$N_x = \rho_x \cdot N_a$

Combine and sort

$N_c + N_\alpha + N_x$
Set 1: Group Memory
Set 2: Local search
Set 3: Global search

Global Search (random)
Local Search (PSO)

Solution Space
Clone

Initial Set (sorted)

Top set ($N_\alpha$)

$N_a$ antibodies

$N_c$ antibodies

$N_c$ antibodies

$N_c$ antibodies

$N_c+N_\alpha$

Iterate

Clone

Mutate

Combine

Combined Set

Top $N_a$