Particle Swam & Electromagnetism-like Mechanism Optimization

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computer automation

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Particle Swam and Electromagnetism-like Mechanism Optimization Methods

- Particle Swam Optimization, PSO
- Electromagnetism-like Mechanism, EM

Particle Swam Optimization, PSO

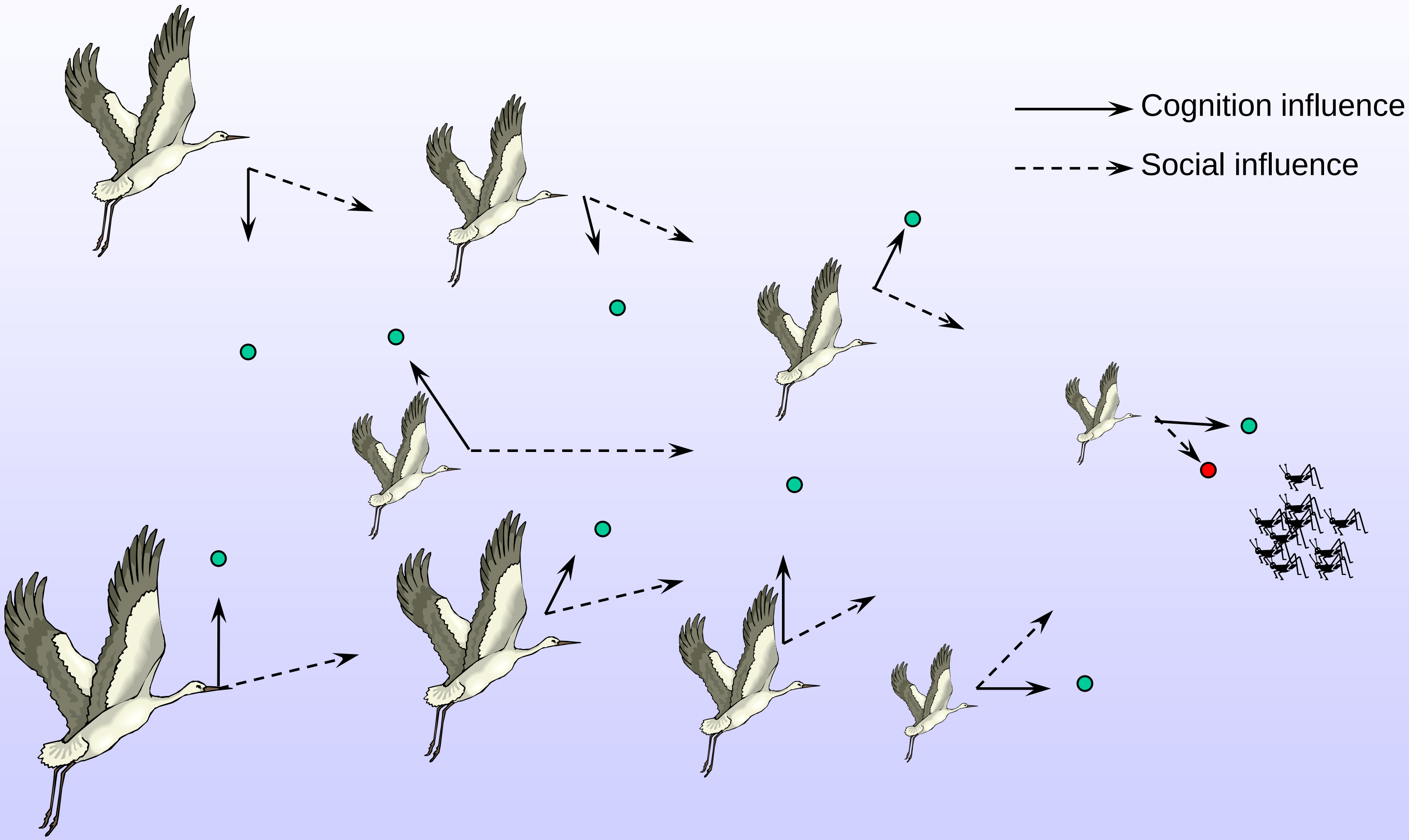
- **Swam Intelligence**
  - **Characteristics of social animals or insects**
  - **Appears in swam behaviors of natural creature**
    - Food search, food hunting, migration against the hostile environment, fight for survival, territory defense, etc.
    - Corporation between individuals
  - **Might have a leader coordinates or instructs the flock**
  - **Might be a communicative and gregarious herd of creature**

PSO

- Proposed by Eberhart and Kennedy (1995)
- Inspired by the food search and hunting behaviors of a flock of birds, fishes, wild animals or a swam of small creature
  - The individual refers to its own experience and the instruction from the swam
- These individuals are treated as particles
  - Each particle represents a solution search agent
  - The position of a particle in the environmental space of the swam is a solution to the optimization problem

- **Memory used in PSO to guide the search**
  - **Particle has individual cognition**
    - Knowing its own solution search experience
  - **Particle has social information or knowledge**
    - Knowing the best solution search experience so far in the whole swam

Swam Behavior



PSO Applications

- Applied to continuous optimization problems
- General discrete PSO is not well-developed yet
  - Few methodologies were proposed for dealing with specific combinatorial optimization problems, such as TSPs, JSPs, etc.

General POS for Continuous Problems

- A general continuous optimization problem without inter-variable constraints

$$\min \ f(\mathbf{x})$$

$$\text{where } \mathbf{x} \in [\mathbf{l}, \mathbf{u}]; \mathbf{x}, \mathbf{l}, \mathbf{u} \in \Re^n; l_i \le x_i \le u_i; i = 1, 2, \ldots, n$$

- Particle swarm: a population of solution agents

$$X = \{\mathbf{x}^1, \mathbf{x}^2, \ldots, \mathbf{x}^m\}, \mathbf{x}^j = [x_1^j x_2^j \cdots x_n^j],$$

$$V = \{\mathbf{v}^1, \mathbf{v}^2, \ldots, \mathbf{v}^m\}, \mathbf{v}^j = [v_1^j v_2^j \cdots v_n^j]$$

  - $\mathbf{x}^j$ is position vector and $\mathbf{v}^j$ is velocity vector for a particle j

$$X' = \{\mathbf{x}'^1, \mathbf{x}'^2, \ldots, \mathbf{x}'^m\}, \mathbf{x}'^j = [x_1'^j x_2'^j \cdots x_n'^j],$$

$$\mathbf{x}^* = [x_1^* x_2^* \cdots x_n^*]$$

  - $\mathbf{x}'^j$: Individual best position of particle j
  - $\mathbf{x}^*$: Global best position; the best solution so far searched by the swam of particles

- **Three steps in PSO algorithm**
  - Assign a initial position and record it as the local best solution for each particle and assign the best solution so far for the swam
  - Compute velocity vectors and move the particles to new positions
  - Update the local and global best positions

Algorithm of PSO

Procedure Particle Swarm Optimization Algorithm

begin

  Initialization(X, $\mathbf{u}$, $\mathbf{l}$)

  Iterations $\leftarrow$ 1

  repeat while *iterations* < t

      MoveParticlestoNewPositions(X, V, c_1, c_2)

        // c_1, c_2 are cognition and social learning factors

      UpdateTheBestPositions(X)

        iterations $\leftarrow$ *iterations* + 1

  end repeat

end

Initialization

- Assign an initial position to each particle
- Evaluate the objective function value for each particle and record the initial position as the local best solution for each particle
- Find the best solution from the local best solution of the particles and assign it as the best solution so far

Initialization

Procedure *Initialization*

begin

for $j = 1$ to m do

for $i = 1$ to n do

$$x_i^j \leftarrow l_i + \sim U(0,\ 1)\ (u_i - l_i)$$

end for

$$\mathbf{x}'^j \leftarrow \mathbf{x}^j$$

$$f'^j \leftarrow f\left(\mathbf{x}'^j\right)$$

end for

$$f^* \leftarrow \min_{j=1,\ldots,m} f'^j$$

$$\mathbf{x}^* \leftarrow \arg\min_{\forall \mathbf{x}^j} f\left(\mathbf{x}^j\right)$$

end

Particle Movement

- Refer to the local and global best positions (solutions) to decide the moving direction
  - c_1: cognition factor
    - Larger value → particle movement follows its own search experience
  - c_2 : social factor
    - Larger value → particle movement follows the swam search experience
- Stochastically assign a moving distance to define the velocity vector for each particle
- Move the particles to their new positions using the computed velocity vectors

Move Particles To New Positions

Procedure *MoveParticlesToNewPositions*

begin

for j =1 to m do

$\alpha \leftarrow c_1 \cdot \sim U(0,1)$

$\beta \leftarrow c_2 \cdot \sim U(0,1)$

for i =1 to n do

$v_i^j \leftarrow \alpha(x_i'^{\,j} - x_i^j) + \beta(x_i^* - x_i^j)$

$x_i^j \leftarrow x_i^j + v_i^j$

$$x_i^j \leftarrow \begin{cases} u_i, \text{if } x_i^j > u_i \\ l_i, \text{if } x_i^j < l_i \\ x_i^j, \text{otherwise} \end{cases}$$

end for

end for

end

Update The Best Solution

- Evaluate the objective function values of all particles
- Update local best position for each particle
- Update the best solution so far

Update The Best Position

Procedure *UpdateTheBestPosition*

begin

    for j =1 to m do

        if $f(\mathbf{x}^j) < f'^j$ then

            $\mathbf{x}'^j \leftarrow \mathbf{x}^j$ and $f'^j \leftarrow f(\mathbf{x}^j)$

            if $f'^j < f^*$ then

                $\mathbf{x}^* \leftarrow \mathbf{x}^j$ and $f^* \leftarrow f'^j$

            end if

        end if

    end for

end

Discussion

- PSO for Discrete optimization problems
  - A few research focused on specific problems
  - Specially tailored movement mechanism

PSO Demo

DEMO

Electromagnetism-like Mechanism Optimization

- Proposed by Birbil and Fang (2003)
- Is a multi-agent heuristic optimization method
- A population of solution agents are defined in the solution space
  - These agents are regarded as chargeable particles
  - The position of each particle represents a solution to the problem
- The position of each particle represents a solution to a continuous optimization problem
- Simulate the attraction and repulsion forces between electrical charged particles in an electromagnetism field

- Electrical charge is assigned to each particle based on the objective function value of the position vector
- Electromagnetic force exerted on each particle is calculated and defined
  - Attraction forces applied to particle with higher charge
  - Repulsion forces applied to particle with lower charge

- The direction of the net force applied to a particle is used to guide the particle movement
- Moving distance is determined stochastically
- Electromagnetic force exertion and particle movement are simulated iteratively until termination condition is met
- The best solution so far is kept updated and serves as the final answer to the problem
- Local search operation can be optionally applied

Primary Operations in EM Optimization

- Initialization
- Local Search (optional)
- Compute Electromagnetic Forces
- Move Particles to New Positions
- Update The Best Solution So Far

Procedure $Electromagnetism\text{-}like\ Heuristic\ Algorithm$

begin

$Initialization(X, \mathbf{u}, \mathbf{l})$

$iterations \leftarrow 1$

repeat while $iterations < t$

$LocalSearch(X, \mathbf{u}, \mathbf{l}, s)$

$F \leftarrow ComputeElectromagneticForces(X)$

$MoveParticlesToNewPositions(X, F)$

$UpdateTheBestSolutionSoFar(\ )$

$iterations \leftarrow iterations + 1$

end repeat

end

Initialization

- **Assign initial position for each particle**
- **Evaluate the objective function values of particles to assign the best solution so far**

Procedure *Initialization*

begin

  for j =1 to m do

    for i =1 to n do

      $x_i^j \leftarrow l_i + \sim U(0, 1)\,(u_i - l_i)$

    end for

  end for

  $f^* \leftarrow \min_{\forall \mathbf{x}^j} f\left(\mathbf{x}^j\right)$

  $\mathbf{x}^* \leftarrow \arg\min_{\forall \mathbf{x}^j} f\left(\mathbf{x}^j\right)$

end

Local Search

- Is an optional procedure
  - Executed to find tune the solution
  - Performed for each particle or the iteration-best particle
- Execute a finite number of neighborhood search trials for a better solution
  - Perturb a small distance in one dimension as a neighbor solution
    - Specify a neighboring step size ρ
  - For each component (coordinate) of each particle, a fix number, s, of perturbations are tried
  - Once a better solution for a particle is found the local search for the particle is complete

Procedure *LocalSearch* (For all particles)

begin

for j =1 to m do

$\phi \leftarrow f\left(\mathbf{x}^j\right)$

for i =1 to n do

$localSearchTrials \leftarrow 1$

repeat while $localSearchTrials < s$

$z \leftarrow x_i^j$

if $\sim U\left(0,1\right) < 0.5$ then $x_i^j \leftarrow x_i^j + \sim U(0,\ 1)\ \rho \max\limits_{k=1,..,n}\left(u_k - l_k\right)$

else $x_i^j \leftarrow x_i^j - \sim U(0,\ 1)\ \rho \max\limits_{k=1,..,n}\left(u_k - l_k\right)$

end if

if $f\left(\mathbf{x}^j\right) < \phi$ then

if $f\left(\mathbf{x}^j\right) < f\left(\mathbf{x}^*\right) \equiv f^*$ then $x^* \leftarrow \mathbf{x}^j$

enf if

jump to the next j //A better solution is found for particle j

else $x_i^j \leftarrow z$ //Resume the original coordinate

end if

$localSearchTrials \leftarrow localSearchTrials + 1$

end repeat

end for

end for

end

Compute Electromagnetic Forces

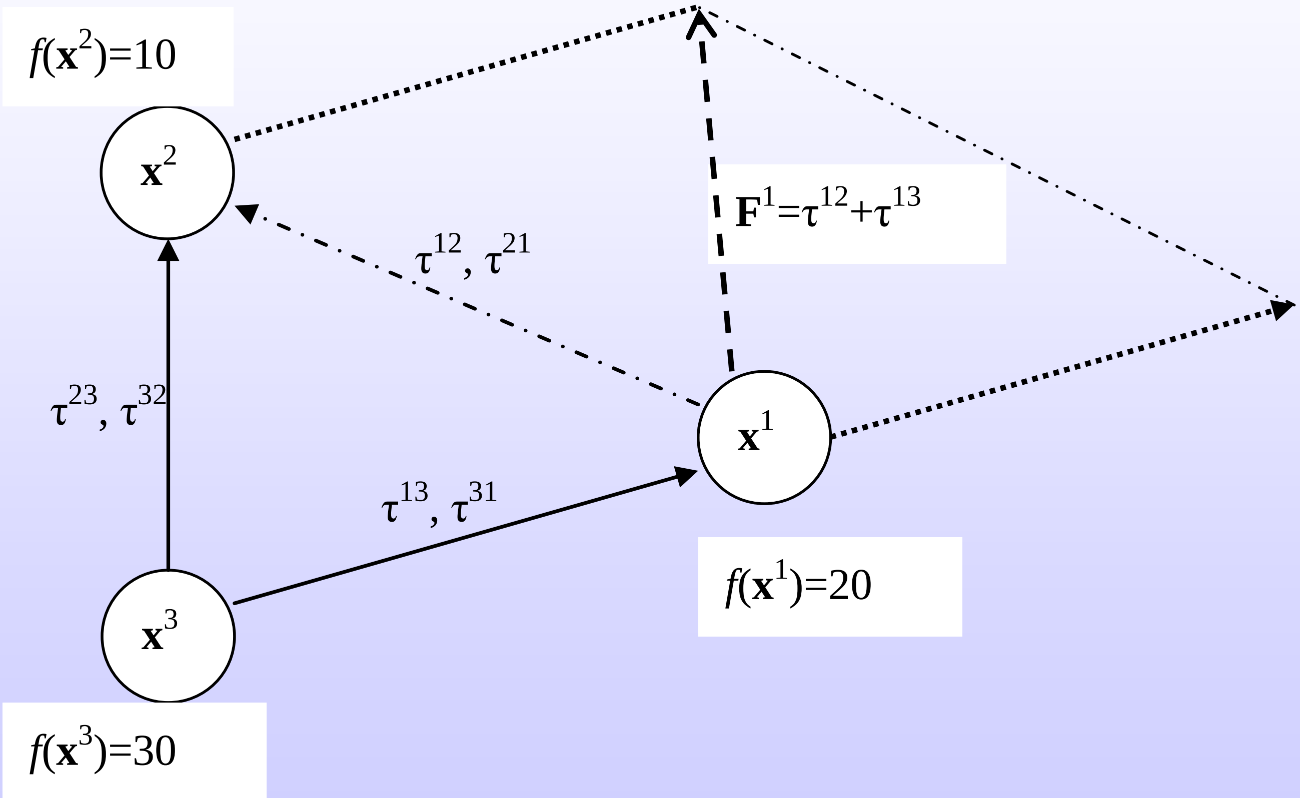
- First assign electrical charge to each particle based on the objective function values
- Higher electrical charge is assigned to the particle with better objective value
  - The best objective function value so far or iteration best value is used for the performance comparison

$$q^j = \exp\left(-n\frac{f(\mathbf{x}^j)-f(\mathbf{x}^*)}{\sum_{k=1}^{m}\left(f(\mathbf{x}^k)-f(\mathbf{x}^*)\right)}\right) \qquad q^j = \exp\left(-n\frac{f(\mathbf{x}^j)-f'}{\sum_{k=1}^{m}\left(f(\mathbf{x}^k)-f'\right)}\right),\ f' = \min_{k=1,\dots,m} f(\mathbf{x}^k)$$

  - n is used in the charge assignment equation
  - An alternative is m

- Attraction force is applied from an lower charged particle to a higher one
- Repulsion force is applied from a higher charged particle to a lower one
- For each particle, exerted electromagnetism force is the sum of repulsion and attraction forces expelled from other particles
- Therefore, lower charged particle will move closer to higher one and higher one will escape from lower one

$$\mathbf{F}^j = \sum_{k=1, k\neq j}^{m} \tau^{jk}, \tau^{jk} = \begin{cases} \dfrac{q^j q^k (\mathbf{x}^j - \mathbf{x}^k)}{\left\|\mathbf{x}^j - \mathbf{x}^k\right\| \left\|\mathbf{x}^j - \mathbf{x}^k\right\|}, if \ f(\mathbf{x}^j) < f(\mathbf{x}^k) \\ \dfrac{q^j q^k (\mathbf{x}^k - \mathbf{x}^j)}{\left\|\mathbf{x}^j - \mathbf{x}^k\right\| \left\|\mathbf{x}^j - \mathbf{x}^k\right\|}, \quad otherwise \end{cases}$$



f(x2)=10
x2
F1=τ12+τ13
τ12, τ21
τ23, τ32
x1
τ13, τ31
f(x1)=20
x3
f(x3)=30

Procedure *ComputeElectromagneticForces*

begin

for $j = 1$ to m do

$$q^j = \exp\left(-n \frac{f(\mathbf{x}^j) - f(\mathbf{x}^*)}{\sum_{k=1}^{m}\left(f(\mathbf{x}^k) - f(\mathbf{x}^*)\right)}\right)$$

end for

for $j = 1$ to m do

$\mathbf{F}^j = \mathbf{0}$

for $k = 1$ to m and $k \neq j$ and $\mathbf{x}^j \neq \mathbf{x}^k$ do

if $f\left(\mathbf{x}^j\right) < f\left(\mathbf{x}^k\right)$ then $\tau^{jk} = \dfrac{q^j q^k (\mathbf{x}^j - \mathbf{x}^k)}{\left\|\mathbf{x}^j - \mathbf{x}^k\right\| \, \left\|\mathbf{x}^j - \mathbf{x}^k\right\|}$

else $\tau^{jk} = \dfrac{q^j q^k (\mathbf{x}^k - \mathbf{x}^j)}{\left\|\mathbf{x}^j - \mathbf{x}^k\right\| \, \left\|\mathbf{x}^j - \mathbf{x}^k\right\|}$

end if

$\mathbf{F}^j \leftarrow \mathbf{F}^j + \tau^{jk}$

end for

end for

end

- In physics the Coulomb’s law states that the electromagnetism force is proportional to the inverse of distance square
- To reduce the computation cost, inverse of distance is used instead
- As noticed, the net force exerted on a particle is the sum of all unit forces expelled by other particles

Move Particles to New Positions

- Use the computed net force as the moving direction for each particle
- The moving distance is determine by a stochastic process
  - A moving factor is used to determine the moving range

$$x_i^j \leftarrow x_i^j + v \cdot \sim U(0,1) \cdot D_i^j \frac{F_i^j}{\| \mathbf{F}^j \|}, \forall i = 1,2,\ldots,n; j = 1,2,\ldots,m$$

$$D_i^j = \begin{cases} u_i - x_i^j, & if \;\; F_i^j \geq 0 \\ x_i^j - l_i, & otherwise \end{cases}$$

v : a moving factor $0 < v < 1$

Update The Best Solution So Far

- After the particle movement, evaluate the objective function value for each particle
- If any position is better than the best position so far, update the best solution so far

$$\mathbf{x}^* \leftarrow \arg\min_{\forall \mathbf{x}^j} f\left(\mathbf{x}^j\right), \; if \;\; \min_{\forall \mathbf{x}^j} f\left(\mathbf{x}^j\right) < f\left(\mathbf{x}^*\right)$$

EM DEMO

DEMO

Discussion

- How to deal with general constrained continuous optimization problem?
  - Soft constraints
  - Hard constraint
- How to deal with complicated problems involving multiple electromagnetism fields
- Similar disadvantages in PSO, how to develop EM optimization for discrete optimization problems
  - Problem specific
  - Challenges:
    - How to define and calculate electromagnetic force
    - How to make particle move to a new position

Programming Assignment (optional)

- Final project candidate
  - Develop a PSO and EM optimization system for general continuous problems (with constraints)
- Research challenge
  - For specific discrete optimization problems, develop pertinent EM operations

EMBOF, EMBOS-E, EMBOS-NET

- A programming framework of EM optimization method for .Net programming
- Developed in NTU GIIE CALB
- Practical applications
  - EMBOS-Excel
  - EMBOS-Net

Final Discussion

- **Other meta heuristic optimization techniques**
  - **Derived from GA**
    - Honey Bee
    - Immune System
- **Invent nature inspired heuristic optimization methods**
  - **For continuous or discrete optimization problems**
    - Water flow like optimization
      - (Yang and Wang, 2008)
    - Others?
      - Amoeba Optimization ? (阿米巴)
      - Yours?

Newly Developed Meta Heuristic Algorithms

- 師法動物習性或行為的啟發式演算法
  - 在近十年內蔚為風潮，上自飛禽下至走獸昆蟲甚至海裡的魚蝦都有學者師法。包括：
  - 貓群優化法**Cat Swarm Optimization (Saha, Ghoshal et al. 2013)**
  - 磷蝦團演算法 **Krill Herd algorithm (Gandomi and Alavi 2012)**
  - 螢火蟲演算法 **Firefly Algorithm (Wang, Guo et al. 2014)**
  - 蝙蝠演算法 **Bat Algorithm (Yang 2011)**
  - 珊瑚優化演算法 **Coral-reef Optimization Algorithm (Salcedo-Sanz, Del Ser et al. 2014)**
  - 布穀鳥搜尋演算法 **Cuckoo Search Algorithm (Nguyen, Vo et al. 2014)**

Newly Developed Meta Heuristic Algorithms (cont.)

- 灰狼優化 **Grey Wolf Optimizer (Mirjalili, Mirjalili et al. 2014)**
- 蛙跳演算法 **Shuffled Frog Leaping Algorithm (Eusuff, Lansey et al. 2006)**
- 海豚回音定位演算法 **Dolphin Echolocation (Kaveh and Farhoudi 2013)**
- 人工蜜蜂屯拓演算法 **Artificial Bee Colony Algorithm (Mernik, Liu et al. 2015)**
- 蜜蜂擇偶優化演算法 **Honeybees Mating Optimization Algorithm (Haddad, Afshar et al. 2006)**
- 蜜蜂結合優化演算法 **Marriage in Honey Bees Optimization Algorithm (Dariane and Farahmandfar 2013)**

Newly Developed Meta Heuristic Algorithms (cont.)

- 部分啟發式演算法的創意來自自然界物理或生物演化定律的觀察
  - 人工免疫系統 **Artificial Immune System (Ying and Lin 2014)**
  - 重力搜尋演算法 **Gravitational Search Algorithm (Shuaib, Kalavathi et al. 2015)**
  - 化學反應優化法 **Chemical Reaction Optimization (Szeto, Wang et al. 2014)**
  - 協和搜尋演算法 **Harmony Search Algorithm (Lee and Geem 2005)**

Newly Developed Meta Heuristic Algorithms (cont.)

- 荷電系統搜尋法 **Charged System Search**
- 雜草叢生優化法 **Invasive Weed Optimization (Jolai, Tavakkoli-Moghaddam et al. 2014)**
- 帝國競爭演算法 **Imperialist Competitive Algorithm (Yousefikhoshbakht and Sedighpour 2013)**
- 磁場荷電系統搜尋法 **Magnetic Charged System Search (Kaveh, Share et al. 2013)**
- 智慧水滴演算法**Intelligent Water Drop Algorithm (Niu, Ong et al. 2013)**
- 光跡優化法 **Ray Optimization (Kaveh and Khayatazad 2012)** 等。

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