Particle Swarm Optimization

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PARTICLE SWARM OPTIMIZATION (PSO)

- Eberhart and Kennedy (1995)
- Multi dimensional search

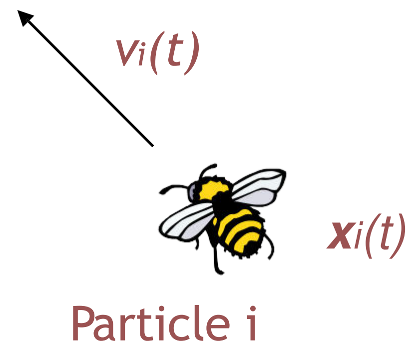
James Kennedy and Russell Eberhart. Particle swarm optimization. In Proceedings of the IEEE International Conference on Neural Networks, volume IV, pages 1942–1948, Piscataway, NJ, 1995

PARTICLE SWARM OPTIMIZATION (PSO)

- Each candidate solution is called **PARTICLE**
- The population is set of vectors and is called **SWARM**
- The particles change their components and move (fly) in a space
- They can **evaluate** their actual position using the function to be optimized
- The function is called **FITNESS EVALUATION**

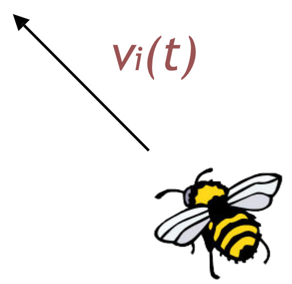
PARTICLE SWARM OPTIMIZATION (PSO)

- Each particle is characterized by
  - Position vector….. $\boldsymbol{x}_i(t)$
  - Velocity vector…...$\boldsymbol{v}_i(t)$



PARTICLE SWARM OPTIMIZATION (PSO)

- Each particle has
  - Individual knowledge ***pbest***
    - its own best-so-far position
  - Social knowledge ***gbest***
    - pbest of its best neighbour



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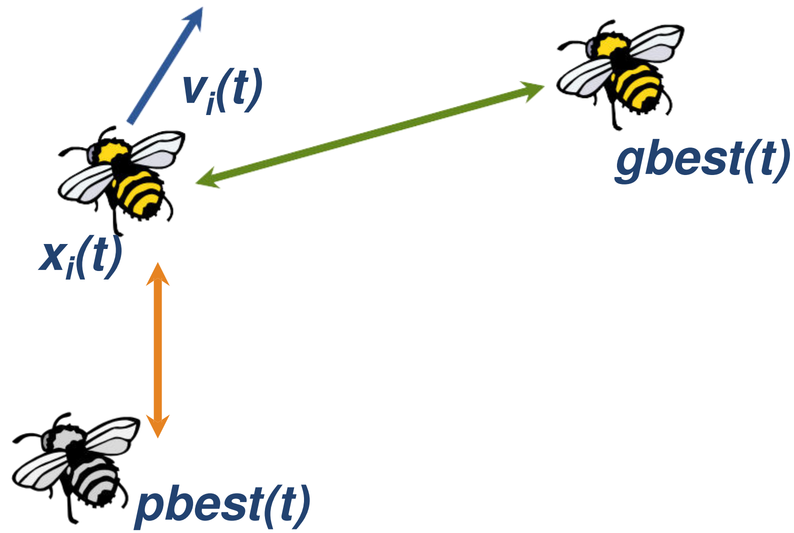
PARTICLE SWARM OPTIMIZATION (PSO)

- Velocity update:

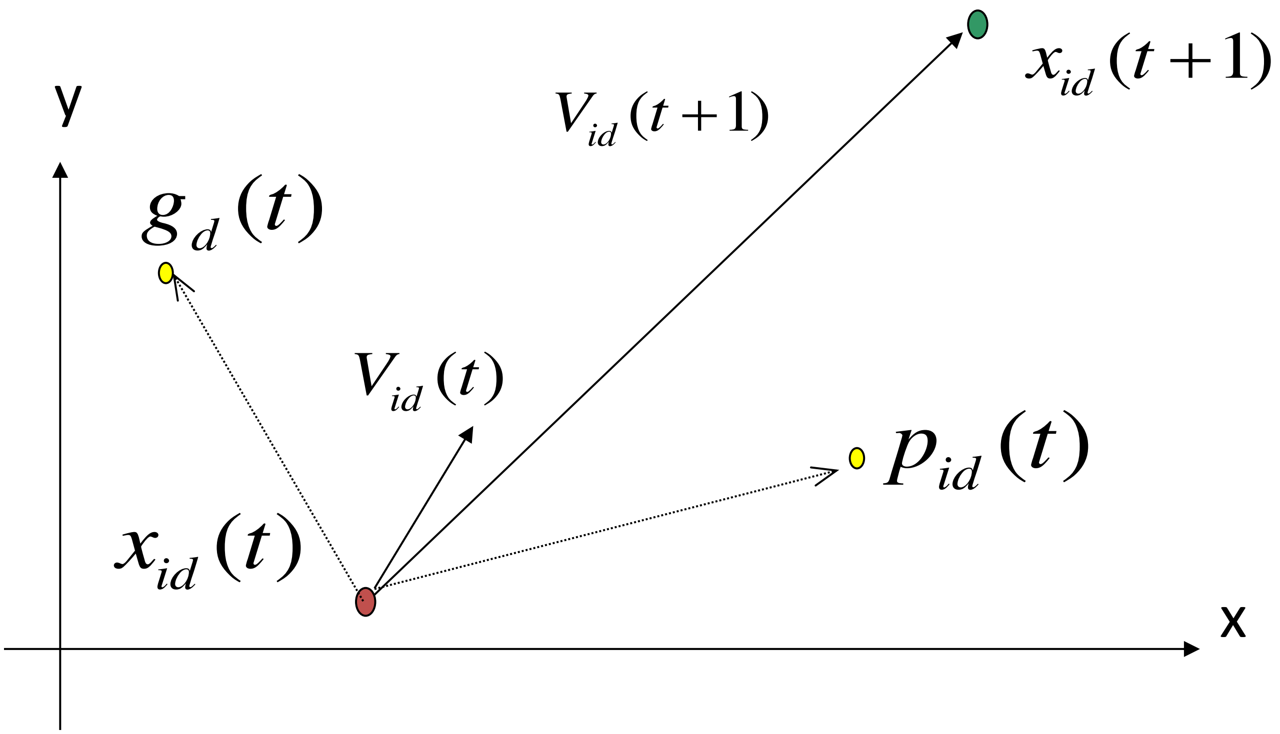
$$v_i(t+1) = w \times v_i(t) + c_1 \times rand \times (pbest_i(t) - x_i(t)) + c_2 \times rand \times (gbest(t) - x_i(t))$$

- Position update:

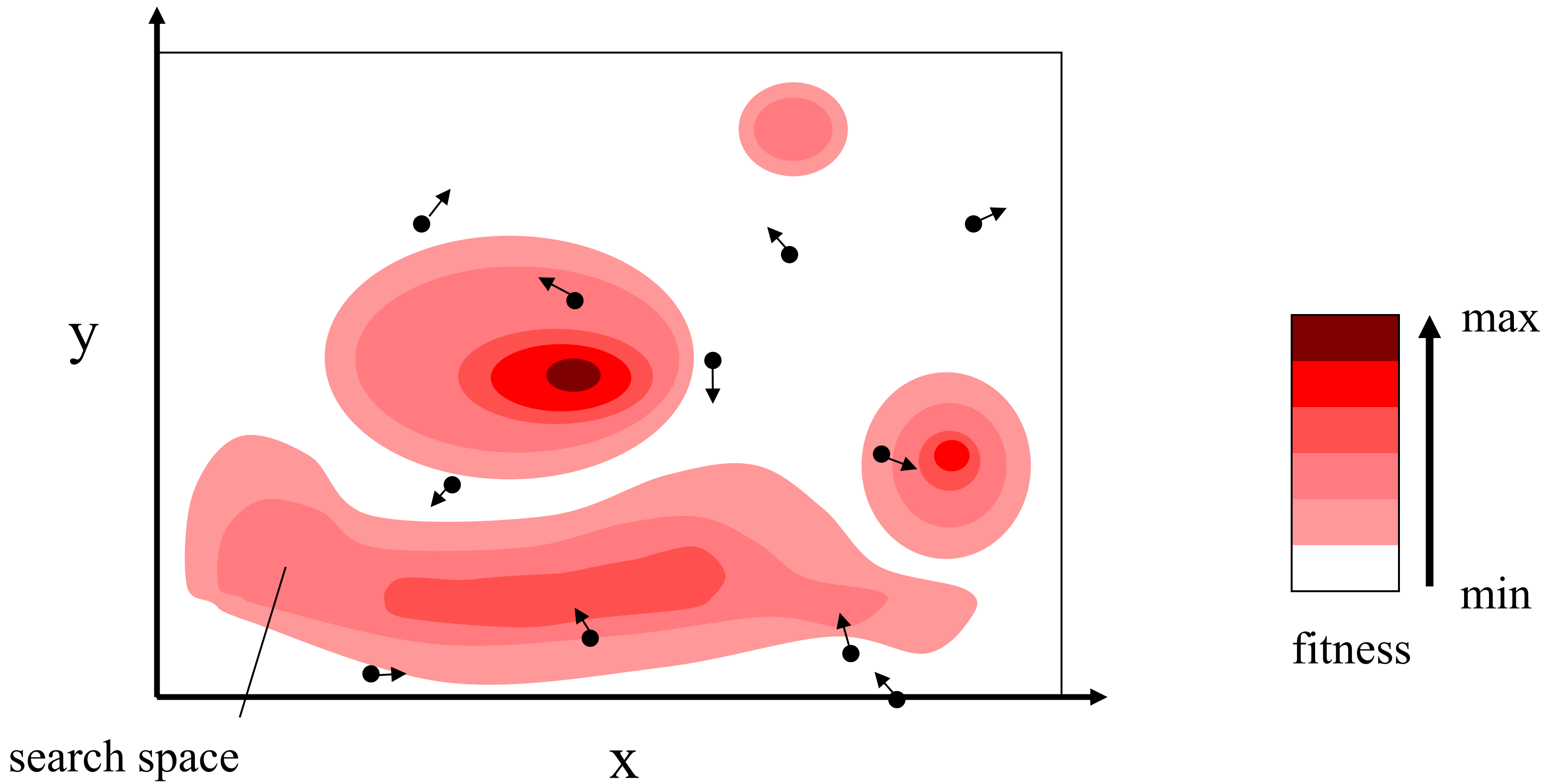
$$x_i(t+1) = x_i(t) + v_i(t+1)$$



LAW OF PARALLELOGRAM



CONVERGENCE OF PSO



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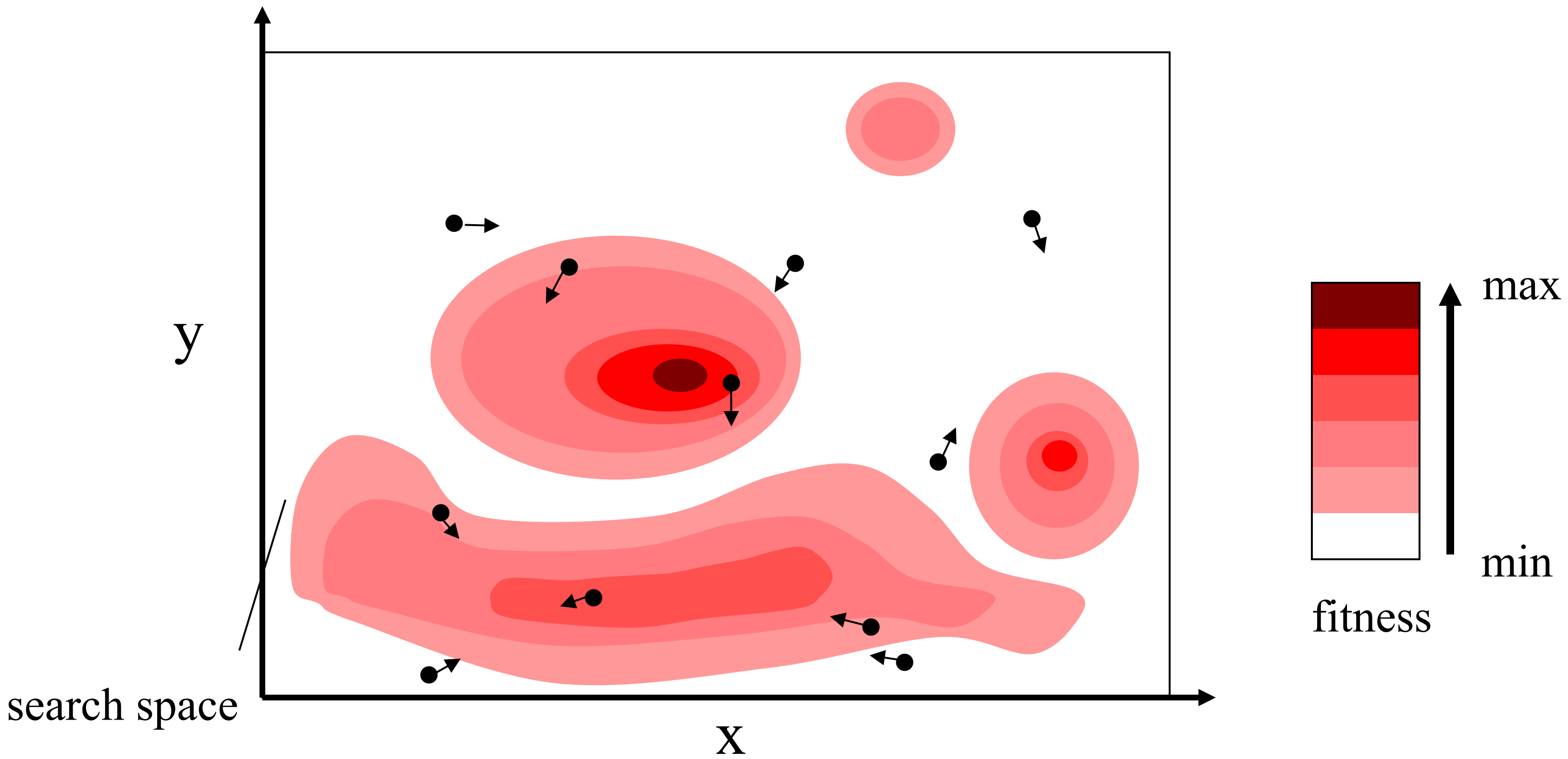

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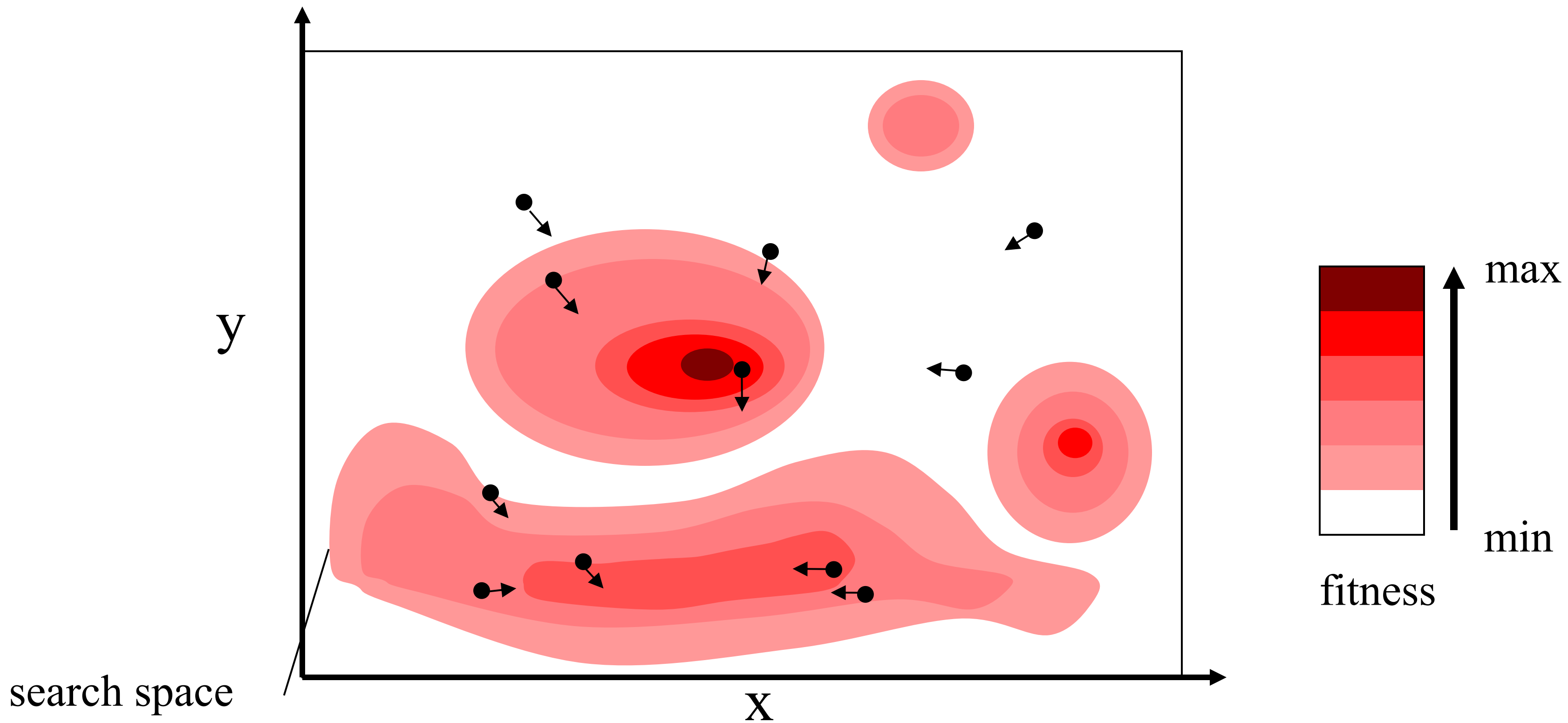

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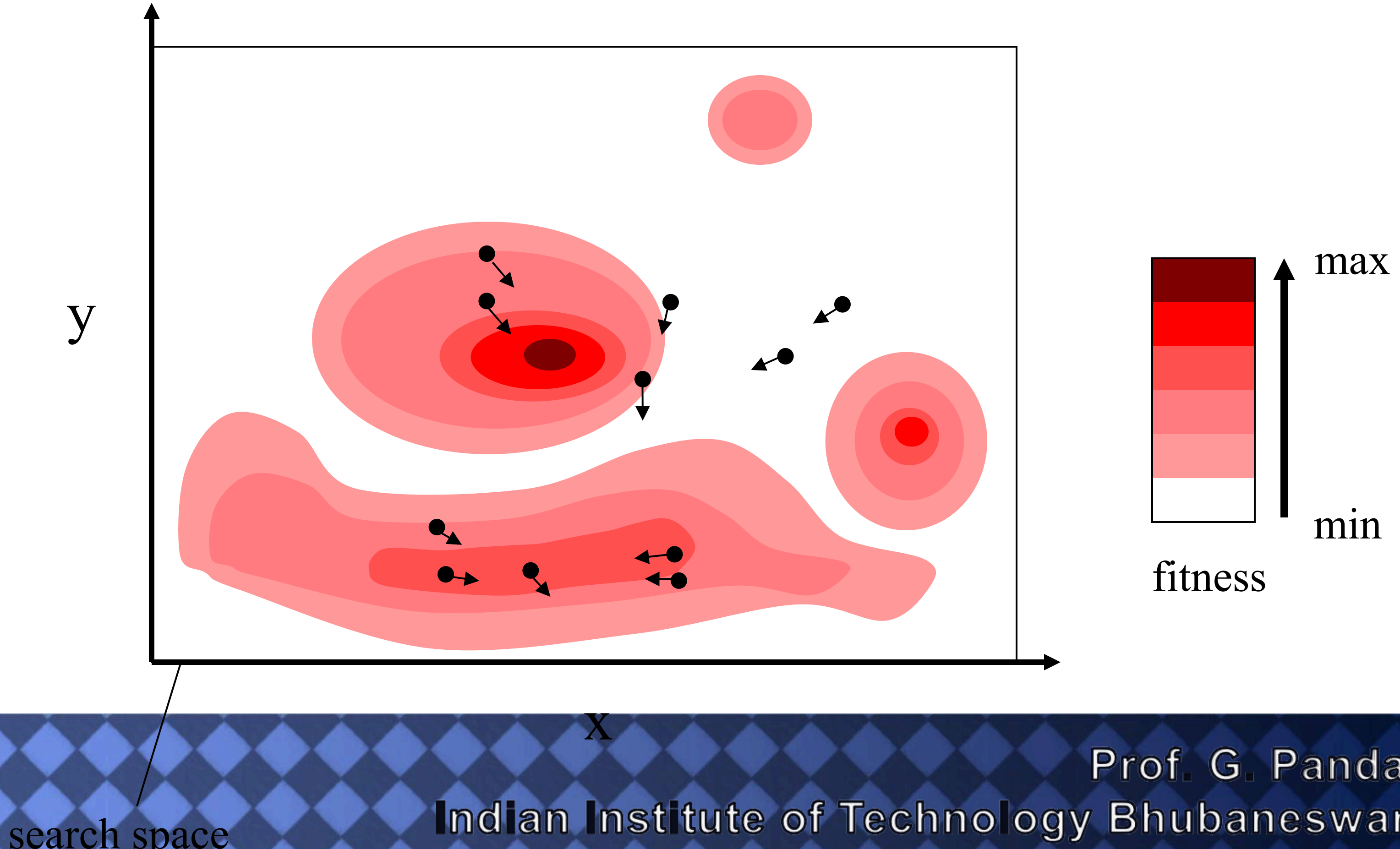

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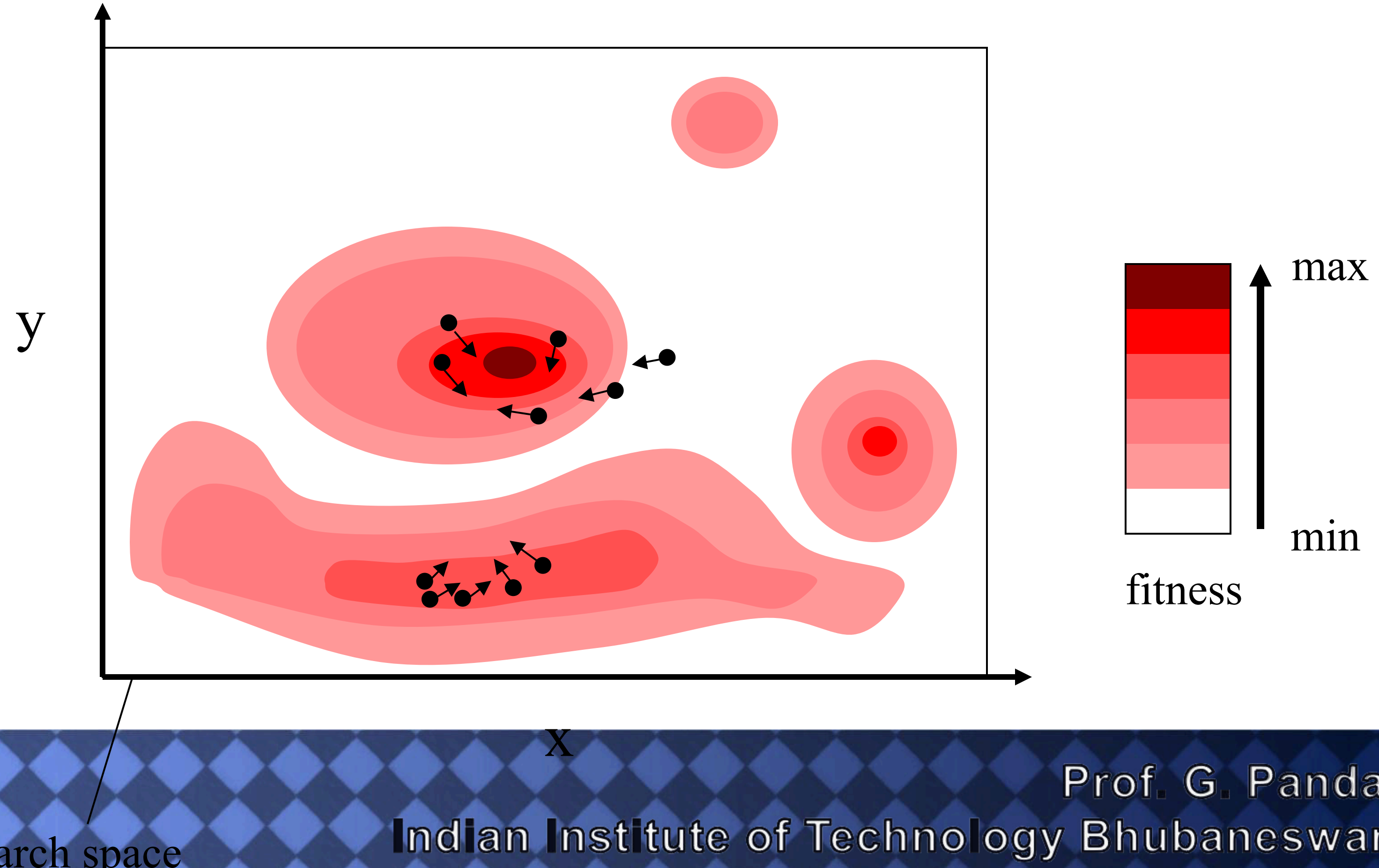

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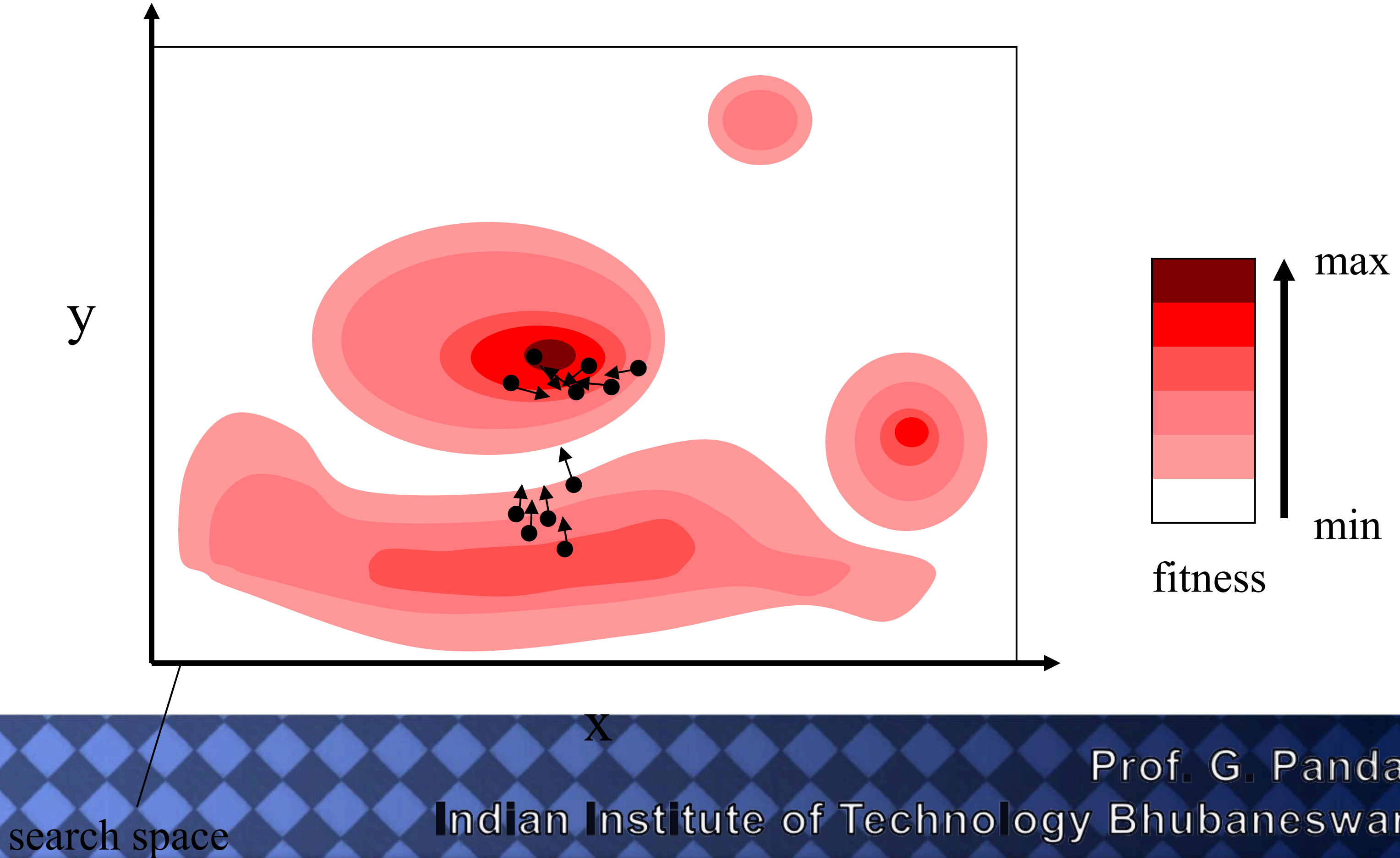

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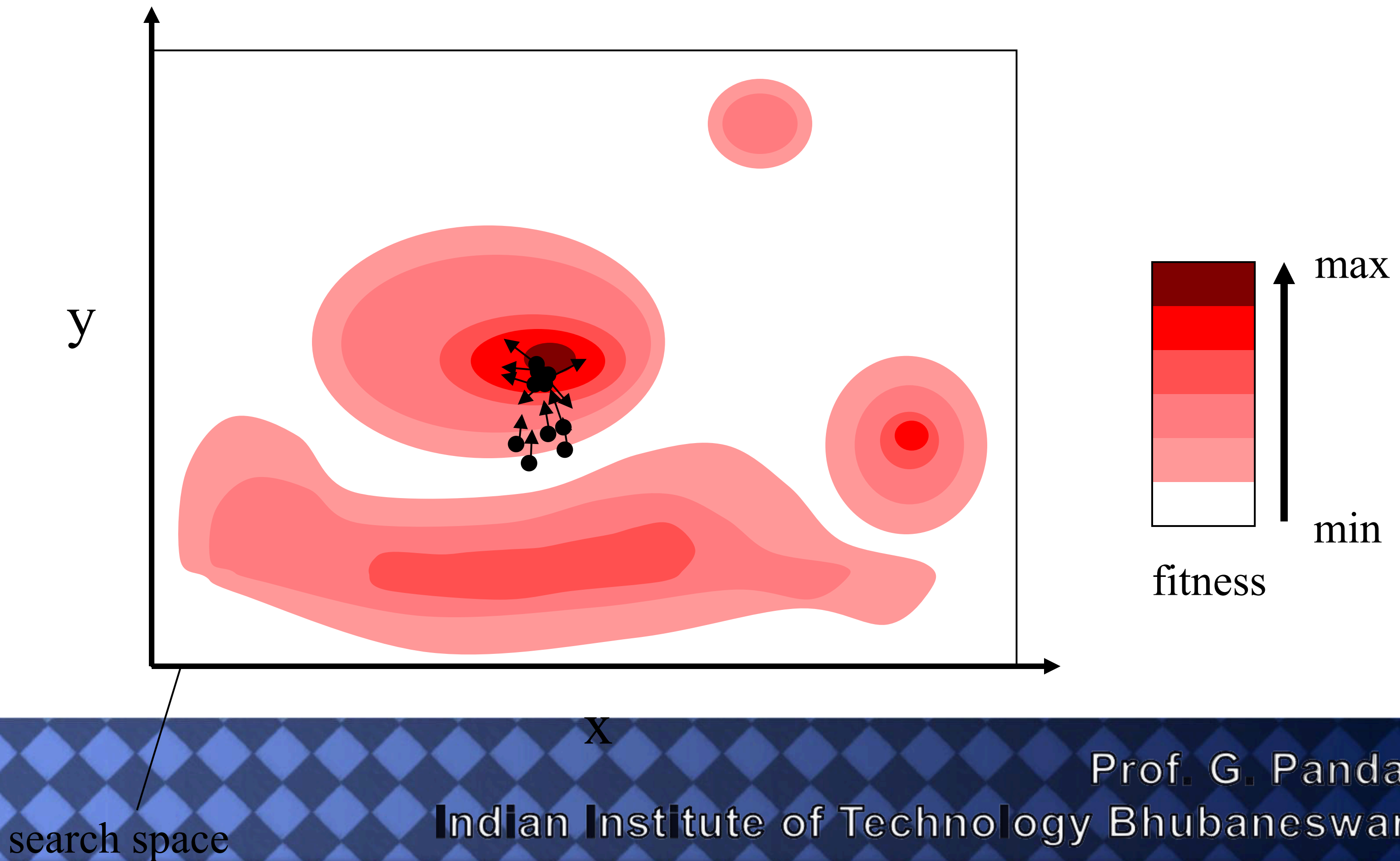

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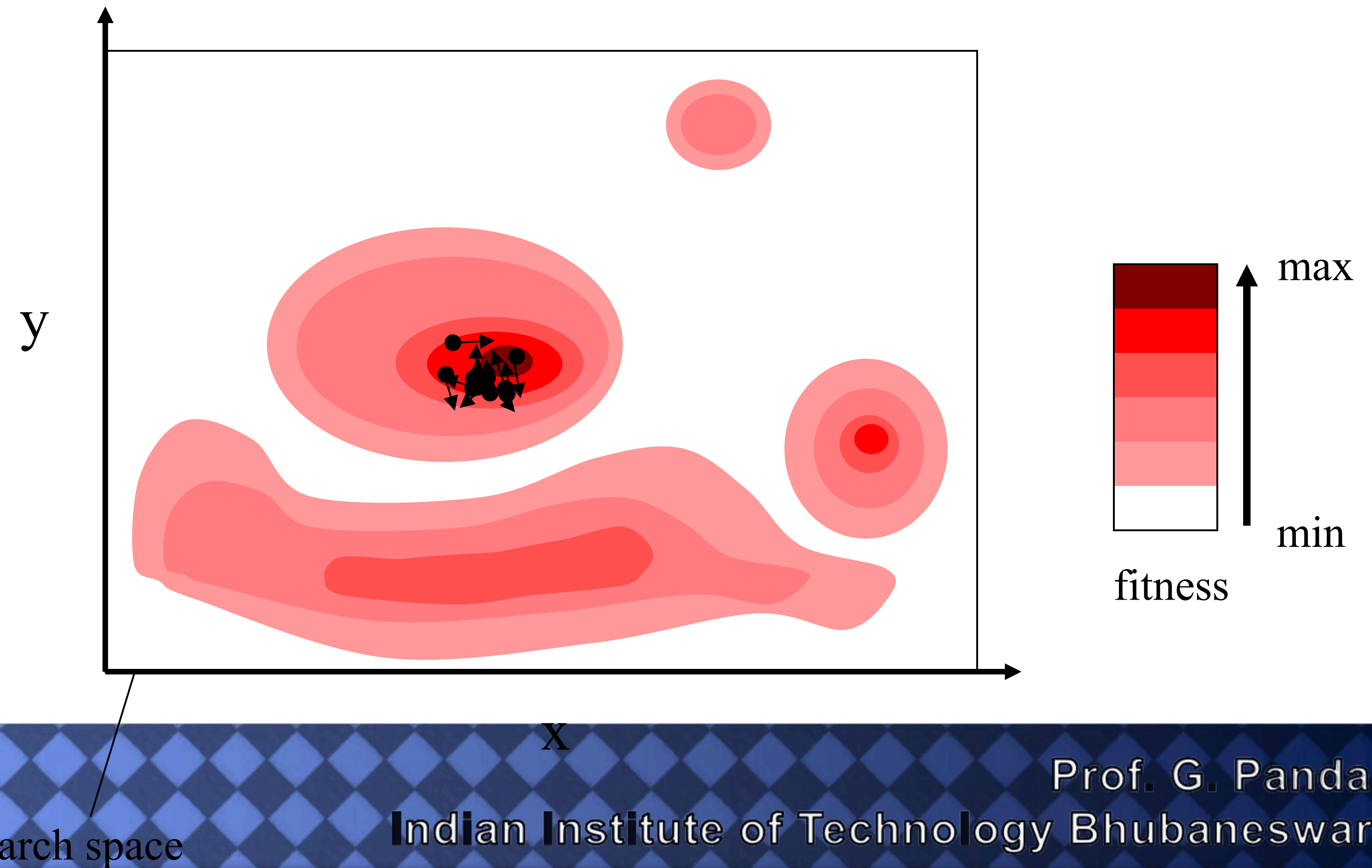
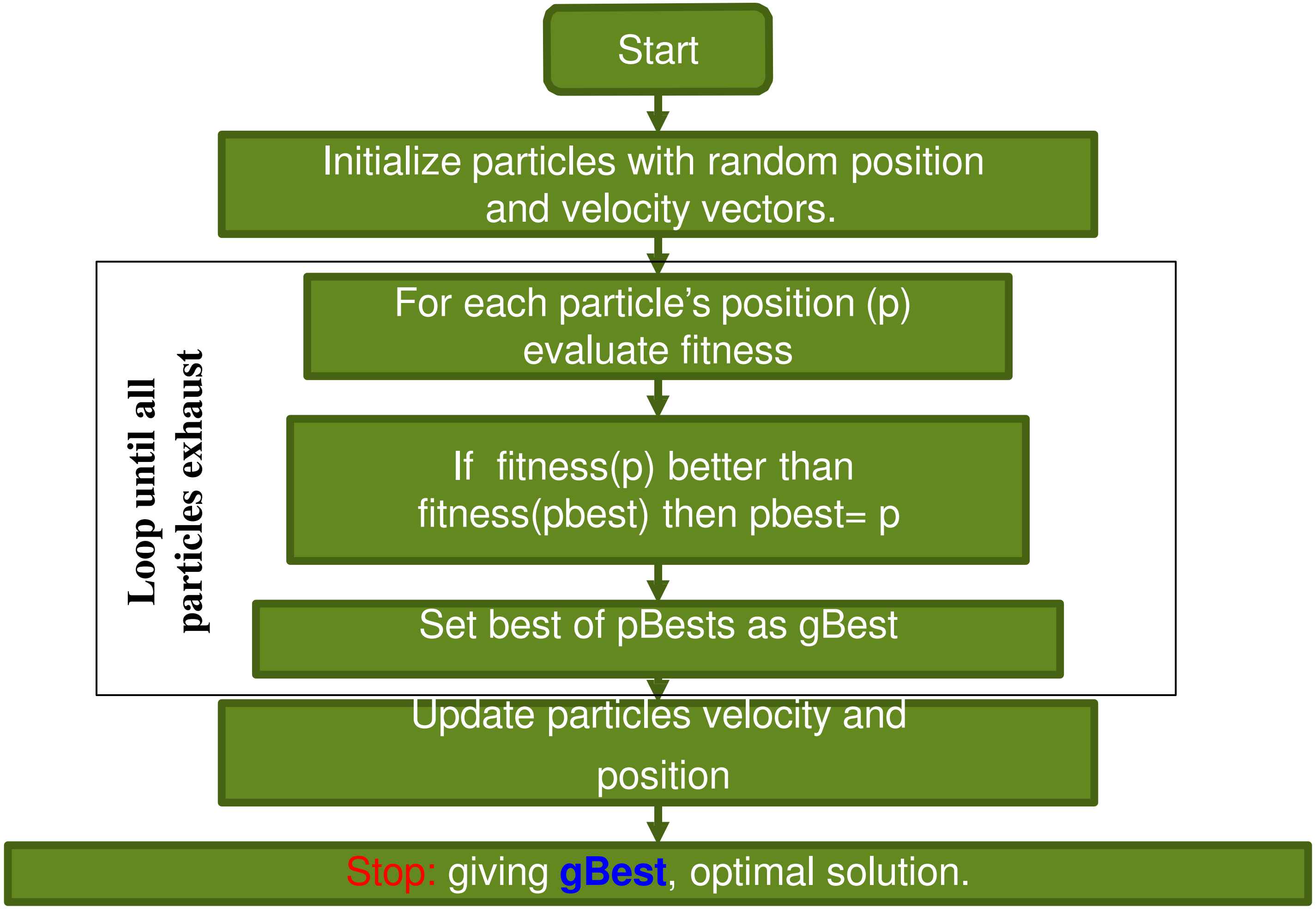
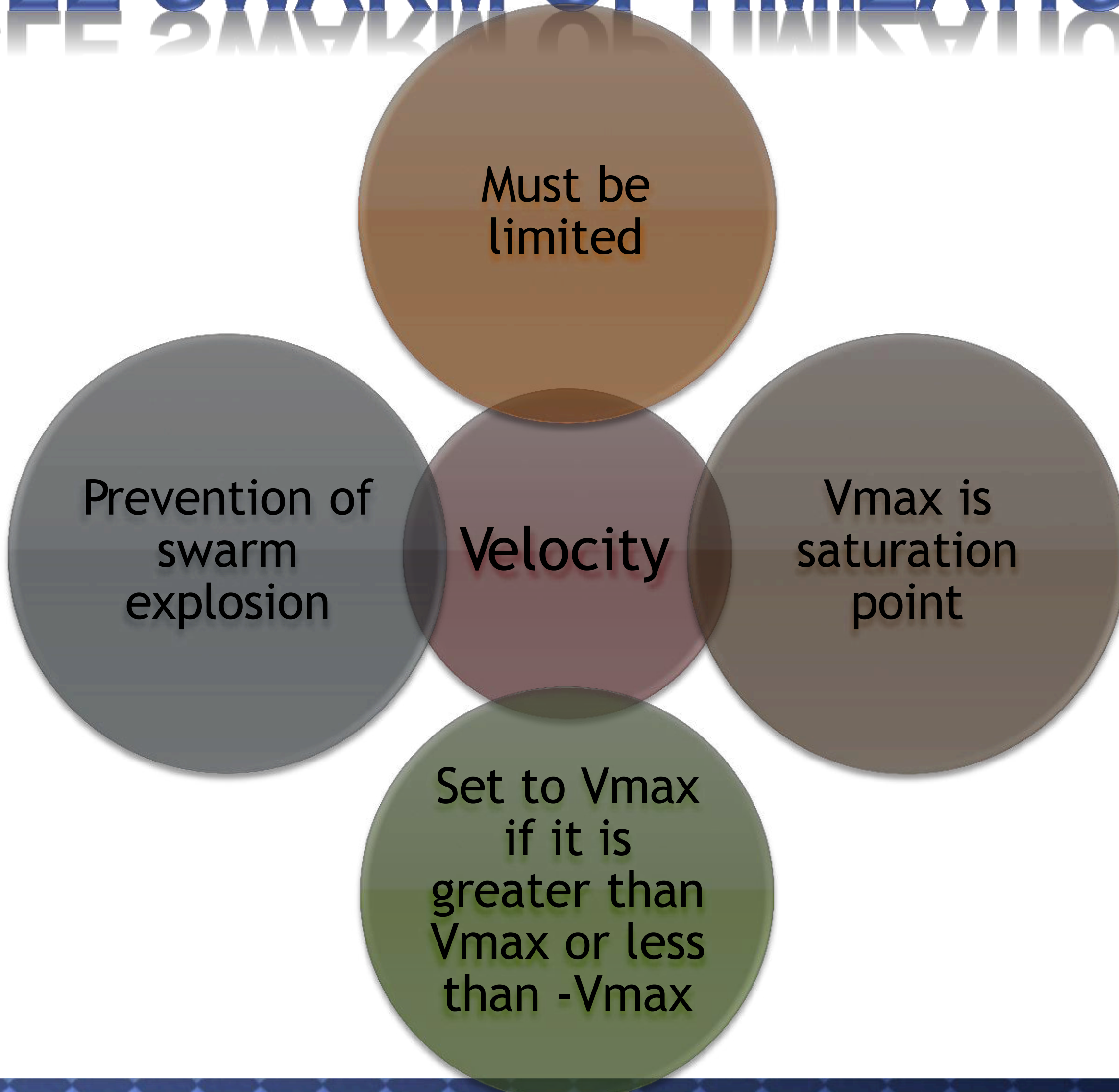


PARTICLE SWARM OPTIMIZATION (PSO)



PARTICLE SWARM OPTIMIZATION (PSO)



PARTICLE SWARM OPTIMIZATION (PSO)

Large W- greater global search ability

Inertial Weight Factor (W)

By linearly decreasing W-gives best PSO performance

Small W- greater local search ability

VARIANTS OF PSO

CLONAL PSO

The best features of PSO and Clonal Selection Principle of Artificial Immune System are combined

velocity of each particle is updated from the knowledge of the previous velocity and W

The location of each particle is then changed in the next search using its updated velocity information.

The location of each particle is changed in the next search using its updated velocity information.

The fitness values of all particles are then evaluated and the overall best location is selected.

PSO WITH LINEARLY DECREASING 'W'

- The linearly decreasing inertia weight, w is given by

$$w(k) = w_0 - \frac{(w_0 - w_1) * k}{I}$$

$K =$ search number

$I =$ max . no. of iterations

$w_0 = 0.9$

$w_1 = 0.4$

PSO WITH CONSTRICTION FACTOR

- Constriction factor guarantees the convergence and improves the convergence velocity.
- The expression for velocity has been modified as

$$V_i(d) = K * V_i(d) + c_1 * rand1_i * (d)\left(p_i(d) - x_i(d)\right) + c_2 * rand2_i(d) * \left(p_g(d) - x_i(d)\right)$$

$$K = \frac{2}{2 - \varphi - \sqrt{\varphi^2 - 4\varphi}}$$

$$\varphi = c_1 + c_2, \varphi \geq 4$$

φ is set to 4.1which gives $c_1=c_2=2.05$ and K=0.729

COMPREHENSIVE LEARNING PSO

Conventional PSO

– Learns simultaneously from pbest and gbest.

– Possibility of trapping in local minima.

CLPSO

Overcomes premature convergence

–Learns from gbest of swarm, pbest of particle and pbest of all other particles at different dimension.

–If D is the total number of Dimension of optimizing problem then, m-dimensions are randomly chosen to learn from the 'gbest', out of the remaining D- m dimensions some learn from a randomly selected particle's 'pbest' and the remaining dimensions learn from its own 'pbest'.

COMPREHENSIVE LEARNING PSO

Initializationof alltheparticlevelocityandpositionrandomly

Settheinitialpositionaspbest(pi,d)andFindgbest(pg,d)

For*n*=1tothemax.Numberofgenerations,

For*i*=1tothepopulationsize,

For*d*=1totheproblemdimensionality,

Updatevelocityaccordingfollowingtoequations:

Ifai(d)==1

$$V_{i,d} = w_n.V_{i,d} + rand(g_{best} - X_{i,d})$$

Else if bi(d)==1

$$V_{i,d} = w_n.V_{i,d} + rand(p_{best,d} - X_{i,d})$$

Else

$$V_{i,d} = w_n.V_{i,d} + rand(p_{bestf,d} - X_{i,d})$$

COMPREHENSIVE LEARNING PSO

Where ai (d) and bi (d) are the deciders of randomly chosen dimension for learning for random particles.

And *gbest* is global best value, *pbest,d* is personal best of ith particle in dth dimension and *pbestf,d* is the personal best value of fth particle in dth dimension

End if

Limit Velocity

Update Position according to equation

$x_{i,d} = x_{i,d} + v_{i,d}$

End- of-d;

Compute fitness of the particle;

Update historical information regarding pbest i and gbest i if needed ;

End-of-*i*;

Terminate if meet the requirements;

End-of-n;

CLONAL PSO

- The best features of **PSO and Clonal Selection Principle** of Artificial Immune System are combined.
- The **local and global best positions** of particles are **not directly used** in deciding their new positions.
- Rather **velocity** of each particle is **updated** from the knowledge of the
- **previous velocity and the variable inertia weights.**
- The **location of each particle is then changed** in the next search using its updated velocity information.
- The **fitness values of all particles are then evaluated** and the overall best location is selected.
- In the next search, **each particle following clonal selection principle occupies the best position achieved so far and then they diversify .**
- As the search process continues all particles proceed towards the best possible location which then represents the desired solution.

CLONAL PSO

ThevelocityupdateequationofCPSObecomes

$$V_{i,d}(k+1) = H(k) * v_{i,d}(k)$$

Where $H(k) = H_o * \frac{(H_0 - H_1)*k}{I}$

k=search number

I=max. no of iterations

$H_0 = .9$

$H_1 = .4$

Position update:

$$X_i(k+1) = X_i(k) + V_{i,d}(k+1)$$

REPULSIVE PSO

$$V_{k+1} = w * V_k + a * R_1 * (x - x_k) + b * R_2 * w * (y - x_k) + c * R_3 * w * z$$

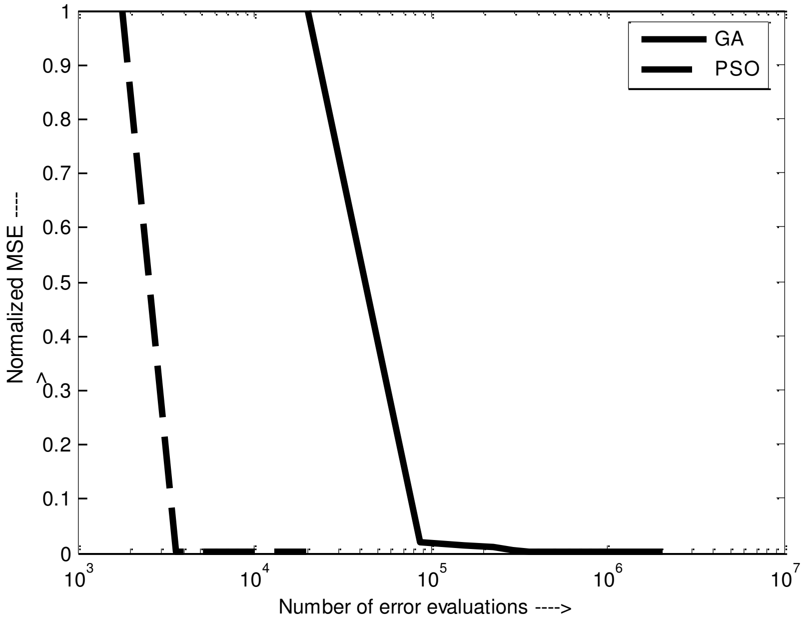
R_1, R_2, R_3 : random numbers between 0 and 1
w : inertia weight between 0.01 and 0.7
x: best position of a particle
y : best position of a randomly chosen other particle from within the swarm
z : a random velocity vector
a, b, c : constants

PSO : SYSTEM IDENTIFICATION

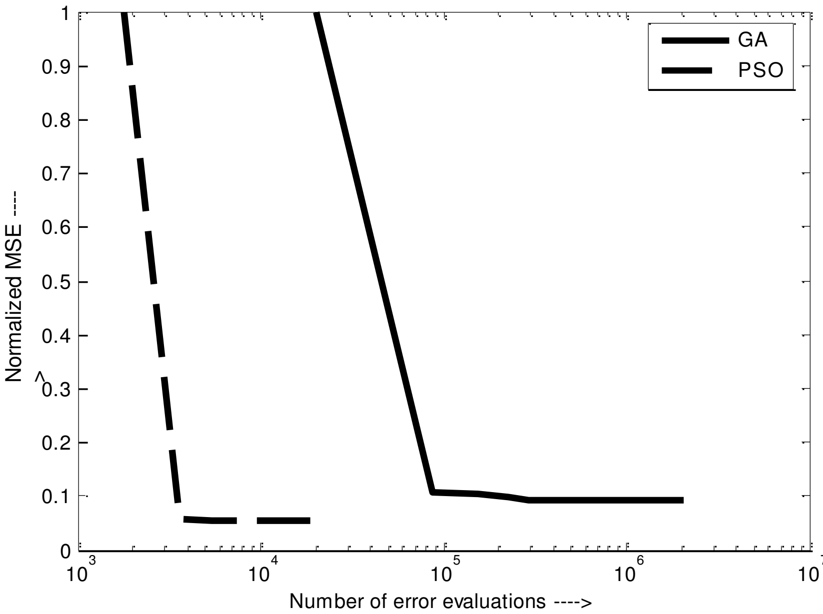
- Input : uniformly distributed white signal in the range of -0.5 to +0.5 and having a variance of 1/12.
- No. of input signal samples : 30
- NSR : -10dB and -30dB
- Parameters of the linear system of the plant [0.2600, 0.9300, 0.2600]
- Nonlinearity associated with the plant : tanh

PSO : SYSTEM IDENTIFICATION

Convergence Characteristics



-30dB



-10dB

PSO : SYSTEM IDENTIFICATION

CPU Time

Nonlinear system	PSO (in second)	GA (in second)
Trained at -30dB	0.3200	13.5090
Trained at -10dB	0.3300	12.4080

PSO : SYSTEM IDENTIFICATION

- Low computational complexity
- Faster convergence during training operation compared to GA based approach
- The present method avoids local minima during training of weights (derivative free training)

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THANK YOU