A Survey on Various Swarm Intelligent Techniques and Applications

[1]Subhashis Mishra, [2]Debashis Mishra, [3]Dr. Madhabananda Das
[1]Dept. of Computer Science, U.N. Autonomous College, Bhubaneswar, India
[2]System Engineer, TATA Consultancy Service Ltd., Bhubaneswar, India
[3]School of Computer Engineering, KIIT University, India

Abstract
Swarm intelligence is an essential research field in today's era which is being used in various applications such as image processing, signal processing, wireless sensor networks etc. swarm intelligence is mainly used to solve various optimization problems. It is the mutual comportment of decentralized and self-organized systems. Here system may refer to natural or artificial group. This paper has the main objective to do an extensive survey on various kind of swarm intelligent technique those are evolved since 1995 till date. It will also focus on various application of the swarm intelligence.

Keywords
Swarm, Swarm Intelligence, Optimization, Particle Swarm Optimization, Ant Colony Optimization, Artificial Bee Colony, Fish School Optimization

I. Introduction
Swarm intelligence is the mutual comportment of decentralized and self-organized systems. Here system may refer to natural or artificial group. Moreover it is a group of homogenous individual, commonly known as agents, intermingle among themselves and with the surrounding environment. In a swarm, agents interacts locally with in the boundary of environment without any kind of centralization. In 1989 it is firstly introduced by G.Beni, Hackwood & J.Wang. Swarm's field of study primarily emphasize on the collective behavior interacting locally with each other as well as with the surrounding. Swarm intelligence represents the idea to control and monitor complex systems interacting among the entities. Its main objective is to enhance the performance and robustness. swarm intelligence is an advancement to the artificial intelligence that is used by mimicking various natural colonies such as colonies of ants, flocking of birds, colonies of fishes, honey bees etc.
The swarm intelligence [9] is characterized by the five identified principles such as-

A. Proximity Principle
This principle is based on feasibility of the population in the term of space and time complexity. It says about the ability of the population to fulfill the objectives in feasible time and space.

B. Quality Principle
In a swarm intelligence based experiments, the population should be able to respond the various quality factors retaining the previous explained proximity principle.

C. Principle of Diverse Response
It means the domain of search area should be vast. Here population should not work in a very narrow channels.

D. Principle of Stability
It is the stability of swarm system in a gradual varying situation of environment. In different word we can say that the system should not alter itself very frequently with the change of environment.

E. Principle of Adaptability
It clearly means the swarm system should be enough adaptable. It can be said as the swarm system should be flexible in its behavior with respect to the computational worth.
As a whole we can say that a swarm intelligent technique is an advanced method of problem solving methodology where a population (group of agents) simultaneously work to solve the problem consuming less space and less time, retaining the quality, working in a vast search area with the stability and adaptability towards the environmental change. A swarm approach is the robust method because if any of agents from these swarm fails then other agents can achieve the objectives. A swarm method has the following advantages over the classical techniques

1. Computational Efficiency
The computational overload of swarm is reduced as it contains multiple processors or agents

2. Reliability
If any of agents fails then also other agents are capable of to solve the problem. The system is not fully reliable on a single agent which indeed increases the reliability of the system.

3. Scalability
A swarm system can increase the number of agents and can also decrease its number as well with in a defined time limit so the system is scalable enough to achieve various problems.

4. Self-organized and Decentralized
All the members of swarm are organized by themselves and there is no fixed leader of the group.

5. Cost Effective
Swarm intelligent technique does not require any special hardware it can run in a minimal environment so it is very cost effective.

II. Particle Swarm Optimization
It is a general opinion, in PSO, a set of randomly created particles in the initial swarm are flown (parameters are defined) through the hyper-dimensional search space (problem space) according to their prior hovering knowledge. The particle position changes within the search space are based on the socio-psychological tendency of individuals to emulate the success of other individuals. To solve the problem each particle represents a potential solution. Based upon the current position of a particle solution is determined. According to the own and neighbor's knowledge, position of each particle is changed. These particles propagate towards the optimal

solution over a number of generations (moves) based on large amount of information about the problem space that is assimilated and shared by all members of the swarm [9]. By simply adjusting the trajectory of each individual towards the own best location (pbest) and best particle of entire swarm (gbest) PSO algorithm finds the global best solution at each time step (generation). In this algorithm, the flying path of each individual in the search space is accustomed by dynamically modifying the velocity of every particle according to its own flying awareness and the flying knowledge of the other particles in the search space.

The position vector and the velocity vector of the ith particle in the n dimensional search space can be expressed as xi = (xi1, xi2, . . . , xin) and vi = (vi1, vi2, . . . , vin) respectively. According to a user defined fitness function, the best position of each particle (which corresponds to the best fitness value obtained by that particle at time t) is pi = (pi1, pi2, . . . , pin) [It is also popularly known as pbest] and the fittest particle found so far in the entire swarm at time t is pg = (pg1, pg2, . . . , pgt)[It is also popularly known as gbest]. Then the new velocities and the new positions of the particles for the next fitness evaluation are calculated at time t+1 using the following two self-updating

Equations given in equation (1).

$$\vartheta id(t+1) = \omega\times\vartheta id(t)+S1\times rand1()\times(Pbestid(t)-xid(t)) +S2\times rand2()\times(Gbest(t)-xid(t)) \quad (1)$$

$$xid(t + 1) = xid(t) + \vartheta id(t) \quad (2)$$

Where rand1 () & rand2 () represents two separately generated uniformly distributed random values in the range [0, 1], ω stands for inertia weight (or inertia factor) which is employed to control the impact of the previous history of velocities on the current velocity of a given particle, S1 & S2 are two constants commonly called as acceleration coefficients (or speed factor or learning factors); S1 known as the cognitive learning factor (or self-confidence factor) which denotes the attraction of that a particle has towards its own success and S2 is the social learning factor (or swarm confidence factor) which designates the attraction of that particle has towards the success of its neighbors. Normally, according to Hassan et al., S1 ranges from 1.5 to 2, S2 ranges from 2 to 2.5 and ω ranges from 0.4 to 1.4. ϑid (t) and xid (t) are the velocity and position of an individual at t iteration respectively. One can observe from equation 2.1 that it has three components which are incorporated via a summation approach and effect the new search direction. The first component is known as current motion influence component [9] which depends on previous velocity and provides the necessary momentum for particles to roam across the search space. The second component is known as cognitive (or particle own memory influence) component which represents the personal thinking of each particle and encourages the particles to move toward their own best positions found so far. The third component is known as social (or swarm influence) component which represents the collaborative effect of the particles, in finding the global optimal solution. This component always pulls the particles toward the global best particle found so far. PSO algorithms are quite promising in the applications to single objective optimization problems as compared to Evolutionary Algorithm (EA) techniques. These are very popular due to their simplicity in their implementations (a few parameters are needed to be tuned). A PSO algorithm is computationally cheap in the updating of the individuals per iteration, as the core updating mechanism in the algorithm relies only on two simple self-updating equations 1 and 2 as compared to using mutation and crossover operations in typical EA which requires a substantial computational cost.

The pseudo code for a basic PSO algorithm [6] is illustrated in Algorithm 1. First, the swarm is initialized. This initialization includes both positions and velocities. The corresponding Pbest of each particle is initialized and the leader is located (the Gbest solution is selected as the leader). Then, for a maximum number of iterations, each particle flies through the search space updating its position (using equations 1 and 2) and its pbest and, finally, the leader is updated too.

Algorithm 1: Basic Single-Objective Particle Swarm Optimization Algorithm

Begin

Parameter settings and initialization of swarm;

Evaluate fitness and locate the leader (i.e. initialize pbest and gbest);

I =0 /* I is iteration count*/

Repeat

For each particle do

Update velocity & position as per equations 1 and 2.;

Evaluate fitness;

Update Pbest;

End

Update leader (i.e. Gbest);

I ++;

Until the stopping criterion is not met, say, I < Imax;

III. Ant Colony Optimization

Ant colony optimization is an artificial intelligent model which mimics the social behavior of ants. Ants are the most social insects which is the best example of the social colonies of working together to achieve a common goal of gathering foods. In a research of double bridge experiments it has been tested by putting two different paths to the food source for ants. it has been observed that ants are choosing the exact shortest path. This intelligent power of ants is modeled to an artificial intelligent technique .ant colony optimization is commonly used as swarm intelligent technique. It is almost similar to motivated behaviors with respect to solve optimization problems. Ants have the foraging behavior as highlighted below [5]

1. Individual ant goes to find food.
2. They don't communicate directly with each other however they communicate indirectly which is known as stigmergy.
3. When one ant successfully find its food source then it immediately returns to the nest (original source of ant). On the way it leaves a chemical fluid elements known as pheromone.
4. Ants are capable of sensing this pheromone and follows route that is attracted by most of the ants.
5. If ants fond any obstacle in the route then they will move randomly in the beginning but later they find the shortest path.

ACO is being used in various application such as scheduling problems, image processing, shortest path finding etc.

IV. Fish School Optimization

This method is introduced in two papers. "A novel algorithm based on fish school behavior" [2] and "fish school search"[1] by C.J.A.B. Filfo et al. it consist of different operators, one is feeding operators and the second one is swimming operators. Feeding operator describes the searching of particle by individual fish. We can say as food is a metaphor for evolution of candidate solution and in the same time swimming is the metaphor for the search process itself. In the process fish gains weight if it finds the food particle successfully and loses weight at every unsuccessful finding. Swimming is primarily driven by feeding needs and in the time it is also influenced by some different reasons like escaping from predator's etc.in his system fish is considered as one possible solution to the search process.

A. Feeding Operator

Let's assume an aquarium where there are food particles scattered in various concentration. Here the boundary of the aquarium is considered as the range of search space and a fish travels independently in it to find the food [1-2]. After a move a fish gains or loses the weight as per successful or unsuccessful finding of food. The new weight of the fish is illustrated by the equation (3).

$$\omega_i^{t+1} = \omega_i^t + \frac{fit(x_i^{t+1}) - fit(x_i^t)}{max\{|\,fit(x_i^{t+1}) - fit(x_i^t)\,|\}} \tag{3}$$

Where ω_i^t is the weight of fish 'i' at 't' iteration, x_i^t is the position of fish 'i' at 't' iteration and fit( ) is the fitness function. This is evaluated in each iteration of FSS [2] One may give a limit to the weight by defining a parameter ω_{max} and the by default weight of a fish is $\omega_{max}/2$.

B. Swimming Operator

Swimming is a natural phenomenon of fish and it is influenced by various reasons. This reasons are classified into three categories as described below

1. Individual Movement

At every cycle it occurs for every fish. Fish always prefers the place having more density. This displacement of the fish inside the aquarium is known as individual step [1, 2] denoted as Δx^{ind}

2. Collective-Inspective Movement

After the individual movement the weighted average is calculated by the equation (3). By the weights of all fishes a direction is resulted and the overall direction is computed [1, 2, 7]. Then the position of individual is updated by the equation (4).

$$x_i^{t+1} = x_i^t + \frac{\sum_{i=1}^{P} \Delta x_i^{ind} \times rand() \times \{fit(x_i^{t+1}) - fit(x_i^t)\}}{\sum_{i=0}^{P} \{fit(x_i^{t+1}) - fit(x_i^t)\}} \tag{4}$$

Where x_i^t is the position of fish 'i' at 't' iteration, Δx_i^{ind} is the displacement of fish 'i' at 't' iteration and P is the population size.

3. Collective-volitive Movement

After performing the above explained movements fish also completes another type of movement that is collective volitive movement. It is generally based on the overall performance on the population. A new parameter (baby center) shown in equation 5 is used in the position of all the fishes to achieve. The direction collective-volitive movement may be inward or outward according to the previously obtained overall weight of the population [7].

$$\beta_t = \frac{\sum_{i=1}^{P} (x_i^t \times \omega_i^t)}{\sum_{i=1}^{P} \omega_i^t} \tag{5}$$

Where β_t is the barycenter of fish school at't' iteration.

V. Updating position of Fish

Now the position of each fish is updated according to the equation 7 if the overall weight decreases or according to the equation 7 if the overall weight increases [7].

$$x_i^{t+1} = x_i^t - S_{vol} \times rand() \times (x_i^t - \beta_t) \tag{6}$$

$$x_i^{t+1} = x_i^t + S_{vol} \times rand() \times (x_i^t - \beta_t) \tag{7}$$

Where S_{vol} stands for volitive step, which is gradually decreased linearly along the FSS iterations.

VI. Conclusion

Other than the above explained swarm intelligent technique there are various other techniques are also evolved in the recent era. This technique has been used in different domains such as wireless sensor networks, image processing [6-9], grid and cloud computing, big data analysis etc. it has been also proven to be time efficient techniques to solve various kind of optimization problem. This technique is also very much reliable to provide the most complex system. Our research is to find the methodology of swarm intelligence to solve different kind of problems related to gray scale and color image processing viz. segmentation, noise reduction etc.

References

[1] C. J. A. B. Filfo, F. B. de Lima Neto, A. J. C. C. Lins, A. I. S. Nascimento, M. P. Lima,"Fish school search", In R. Ching, editor, Nature-Inspired Algorithm for Optimization, Vol. 193, pp. 261–277. Springer, 2009.
[2] C. J. A. B. Filho, F. B. de Lima Neto, A. J. C. C. Lins, A. I. S. Nascimento, M. P. Lima,"A novel search algorithm based on fish school behavior", pp. 2646–2651. IEEE International Conference on Systems, Man and Cybernetics (SMC), 2008.
[3] J. Kennedy, R. Eberhart,"Particle swarm optimization, developments, applications and resources", IEEE, 2001.
[4] J. Kennedy, R. Eberhart,"Particle swarm optimization", IEEE, pp. 1942–1948, 1995.
[5] M. Dorigo, T. Stutzle,"Ant Colony Optimization, A Bradford Book", The MIT Press, Cambridge, Massachusetts, London, England, 2004.
[6] D Mishra, I Bose, M Das, U. C. De,"Medical Image Thresholding Using Particle swarm Optimization", Intelligent Computing, Communication and Devices, Advances in Intelligent Systems and Computing, Springer, Vol. 308, pp. 379-383, 2015.
[7] D Mishra, I Bose, U.C. De," Fish School Search approach to find optimized thresholds in gray-scale image", 5th International Conference on Computing, Communication and Networking Technologies (ICCCNT), IEEE, Heifei, China.
[8] D Mishra, I Bose, U.C. De, M Das,"Multilevel Image Thresholding using Particle Swarm Optimization", International Journal of Engineering and Technology (IJET), Vol. 6, No. 2, pp. 1204 – 1211.

[9] BSP Mishra, E. Kim, G.C. Bang, S. Dehuri, S B. Cho. "Weapon target assignment problem: Multi-objective formulation, optimisation using MOPSO and TOPSIS", International Journal of Intelligent Defence Support Systems, 2015.

Subhashis Mishra is continuing his Master of Science (M.Sc.) in computer science at UN Autonomous College, Cuttack, India. He is continuing his final semester research (thesis) required for the degree award, under the guidance of Debashis Mishra, System Engineer, TATA Consultancy Service Ltd., Bhubaneswar and Prof. (Dr.) Madahabanada Das, Sr. Prof., KIIT University, BBSR.

Debashis Mishra is now continuing as System Engineer in TATA Consultancy Service Ltd. He has served as an Oracle EBS analyst for various projects in the organization. He has completed his Master of Technology (M.Tech.) in Computer Science and Engineering from KIIT University in 2014. During his MTech, he has worked in Swarm intelligence and image processing and is having various research publications over the topic.

Prof. (Dr.) Madhabananda Das is currently working as Senior Professor in the school of Computer Engineering, KIIT University, Bhubaneswar. He is awarded Ph.D. in Multi-objective swarm intelligence. He is currently holds president position of Robotic and artificial intelligence society, held at KIIT University. More than 10 PhD scholars and 70 MTech scholars are awarded under his guidance till date.