Information Sharing in Swarm Intelligence Techniques: A Perspective Application for Natural Terrain Feature Elicitation

Lavika Goel
Delhi Technological University
Computer Engineering Department
Delhi, India

Daya Gupta
Delhi Technological University
Computer Engineering Department
Delhi, India

V. K. Panchal
Defence Terrain Research Laboratory
DRDO, Delhi, India

ABSTRACT
Swarm intelligence (SI) is an Artificial Intelligence technique based on the study of collective behaviour in decentralized, self-organizing systems. It enables relatively simple agents to collectively perform complex tasks, which could not be performed by individual agents separately. Particles can interact either directly or indirectly (through the environment). The key to maintain global, self-organized behaviour is social interaction i.e. information sharing between the system's individuals. Hence, information sharing is essential in swarm intelligence. In this paper, we highlight how the concept of information sharing in various swarm-based approaches can be utilised as a perspective application towards the elicitation of natural terrain features. The paper provides a mathematical formulation of the concept of information sharing in each of the swarm intelligence techniques of Biogeography based optimization (BBO), Ant Colony Optimization (ACO), Particle Swarm optimization (PSO) and Bee Colony Optimization (BCO) which are the major constituents of the SI techniques that have been used till date for classifying topographical facets over natural terrain.

Keywords
Swarm Intelligence (SI), Information Sharing, BBO (Biogeography Based Optimisation), ACO (Ant Colony Optimisation), PSO (Particle Swarm Optimisation), BCO (Bee Colony Optimisation).

1. INTRODUCTION
SI techniques were adopted because they are adaptable, evolvable, resilient and easy to implement. Unlike conventional workgroups that have standard operating procedures to react to predetermined stimuli, swarms can adjust to new situations. Countless novel possibilities exist in SI, which is an interplay of the activities of many interlinked individuals. Evolution is the result of adaptation. In swarm systems, individual variation and imperfection lead to perpetual novelty, which leads to evolution. A Swarm is highly adaptable and evolves quickly. Hence, failures tend to be minimal and it maintains its resilience. Swarm-Based Approaches can be applied to a diverse set of problems because it requires an overview and not an extensive description of the problem. Most real-life problems have components of both imprecision and bias, and the general rule is that the greater the imprecision component (relative to the bias component), the greater the potential for SI solutions [14].

Various swarm based approaches have been developed till now. Particles involved in these techniques can either interact directly through waggle dancing (BCO), global-best positions (PSO) etc. Or indirectly through the environment via pheromones (ACO), migration of SIV's between candidate solutions (BBO) etc. Ant colony optimization was proposed by Marco Dorigo [5] in 1992. ACO has since been applied to many search, optimisation and anticipatory problems [10]. Similarly, particle swarm optimization algorithm which simulates the social behaviour of bird flocking or fish schooling was introduced by Eberhart and Kennedy [9] in 1995. PSO is a population based stochastic optimization technique and is well adapted to the optimization of nonlinear functions in multidimensional space [15]. PSO has been applied to several real-world problems. Likewise, motivated by the foraging behaviour of honeybees, researchers Riley et al., Karaboga and Basturk (2005) [2], proposed artificial bee colony algorithm for solving various optimization problems [3, 4, 6]. This algorithm is easy to implement and robust. Also a novel approach is added in this category called biogeography-based optimization and was recently proposed by Dan Simon (2008) [1].The key to maintaining global, self-organized behaviour is social interaction. The fundamental principle of these techniques is cooperation and sharing of knowledge. The basis of the increased intelligence is the shared information discovered individually and communicated to the swarm by different mechanisms of social interaction. In this way, intelligent solutions to problems naturally emerge from the self-organization and communication among simple individuals.

In this paper, the first section is an introduction highlighting why we're studying swarm intelligence and information sharing and the milestones that have been reached in this field. The second section gives details of SI. The third section discusses the adaptive implementation of the concept of information sharing for natural terrain feature elicitation in various Swarm-based approaches like BBO, ACO, PSO and BCO. The last section presents concluding remarks and the future scope of the discussion.

2. SWARM INTELLIGENCE

Swarm intelligence (SI) refers to a kind of problem-solving ability that emerges by the interaction of simple information-processing units. The information-processing units that compose a swarm can be animate, mechanical, computational, or mathematical; they can be insects, birds, or human beings; they can be array elements, robots, or standalone workstations; they can be real or imaginary. Examples of systems studied by swarm intelligence are colonies of ants and termites, schools of fish, flocks of birds, herds of land animals.

Swarm intelligence offers researchers and scientists a tool for solving very difficult NP class problems. Swarm intelligence's ability to solve these problems leads to various practical real world applications such as, traffic routing, networking, games, industry, robotics and controlling unmanned vehicles. The European Space Agency is thinking about an orbital swarm for self assembly and interferometry. NASA is investigating the use of swarm technology for planetary mapping.

3. INFORMATION SHARING IN SI TECHNIQUES: AN APPLICATION TOWARDS NATURAL TERRAIN FEATURE ELICITATION

Some populations of individuals propose solutions to a problem, and then are able to refine those solutions by interacting with their peers, picking up suggestions from their neighbours, and adjusting their own patterns of variables. SI systems are typically made up of a population of simple agents interacting locally with one another and with their environment. Although there is normally no centralized control structure dictating how individual agents should behave; local interactions between such agents often lead to the emergence of global behaviour.

The interactions among the individuals are based on simple behavioural rules that exploit only local information that the individuals exchange directly or via the environment. The overall behaviour of the system results from the interactions of individuals with each other and with their environment i.e. the group behaviour self-organizes. The characterizing property of a swarm intelligence system is its ability to act in a coordinated way without the presence of a coordinator or of an external controller. Notwithstanding the lack of individuals in charge of the group, the swarm as a whole can show intelligent behaviour. This section discusses the information sharing in various swarm based techniques.

Figure 1 presents an overview of this section. The figure describes each of the SI techniques which are based on the information sharing concept along with the heuristic function which forms the base of the mathematical framework for adapting the respective SI technique to suit our purpose of natural terrain feature elicitation. Each of these heuristic equations and the adaptive framework for each of the SI techniques is described in detail in the respective subsections below.

3.1. Biogeography Based Optimization (BBO)

This section discusses how the concept of information sharing finds its application in BBO has been used for elicitation of topographical facets. The major steps for image clustering and heuristic method (HSI) implementation, which form the pillars of the concept of adaptive application of information sharing for terrain features elicitation, are explained next [11]. The m-bands image is clustered into Hi, using rough set theory. The parameters of clustering are NIR and MIR bands. The resultant clusters or the habitats Hi, are species in universal habitat as depicted in figure 2 below.

These species are migrated to the suitable habitats i.e. feature islands. These habitats are actually the decisions, for the resultant different feature groups. The heuristic method decides which species are moved to which habitat using a fitness function [1, 7, 8]. The fitness function is actually the information that is shared among all the habitats in order to decide the suitable habitat for migration of each species. Here we have used mean of standard deviation as fitness function. This function for a specific class takes up the corresponding training sets and then calculates the required function values, which further helps to decide the most suitable habitat.

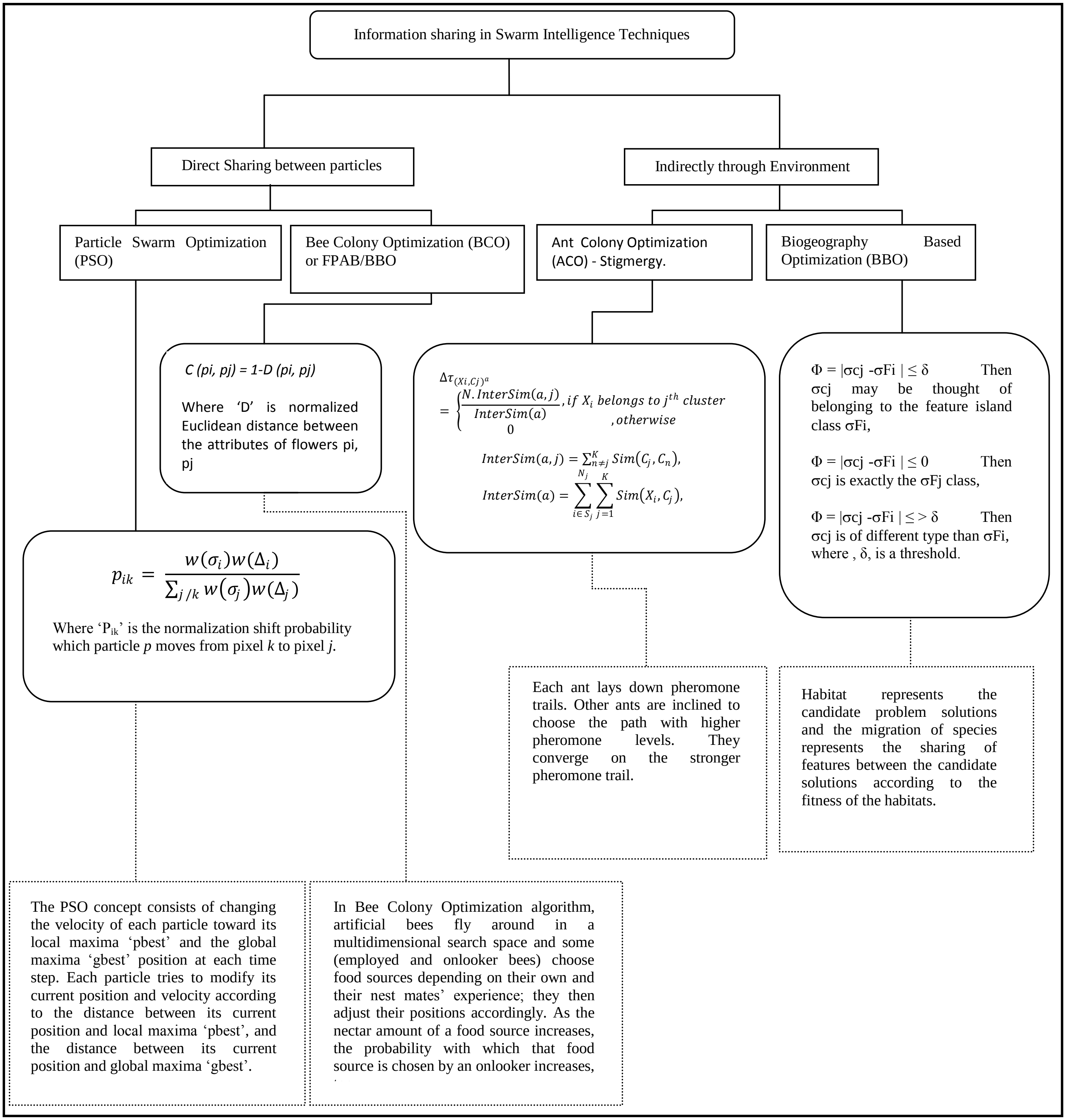

Figure 1: An overview of information sharing for natural terrain feature elicitation in Swarm-Based Approaches

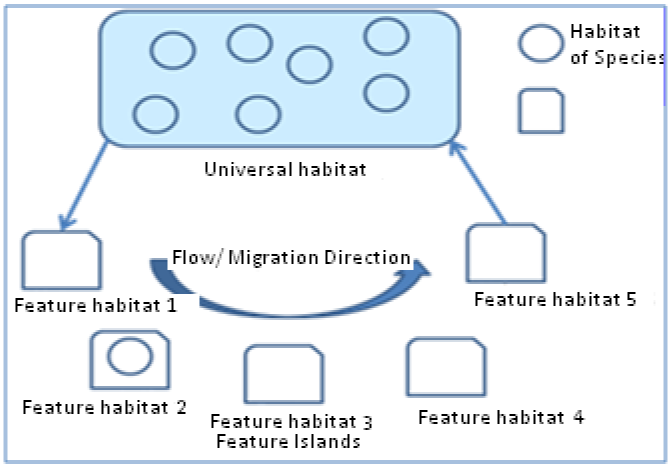

Figure 2: Initial State of the ecosystem

Let σF_i, be the average of the standard deviations of any of the feature islands.

$\sigma F_i = (\sigma_{1_i} + \sigma_{2_i} + \sigma_{3_i} + \sigma_{4_i} + \ldots\ldots + \sigma_{m_i})/m$

Where $\sigma_{1_i}, \sigma_{2_i}, \sigma_{3_i}, \sigma_{4_i}, \ldots\ldots, \sigma_{m_i}$ are the standard deviations of the DN values of each of the m bands respectively of the ith feature island.

Similarly, let the average of the standard deviation of the species habitat C_j from H_i of the Universal Habitat $\mathbf{\Pi}$ be represented by:

$$\sigma_{c_j} = (\sigma_{1_j} + \sigma_{2_j} + \sigma_{3_j} + \sigma_{4_j} + \ldots\ldots + \sigma_{m_j})/m$$

Then the heuristic function Φ be defined as

$\Phi = |\sigma_{c_j} - \sigma_{F_i}| \leq \delta$ Then σc_j may be thought of belonging to the feature island class σF_i,

$\Phi = |\sigma_{c_j} - \sigma_{F_i}| \leq 0$ Then σc_j is exactly the σF_j class,

$\Phi = |\sigma_{c_j} - \sigma_{F_i}| \leq > \delta$ Then σc_j is of different type than σF_i,

where, δ, is a threshold.

Also, heuristic function makes use of a specific threshold value. For higher accuracy, the threshold value should be low. But with low threshold value the number of generations rises at a rapid pace. If for a species, no suitable habitat is found in the current generation, it implies that there are a large number of features in the given section of the image (defined as a species). This unclassified cluster migrates to the universal habitat. Here it is again classified using rough set theory. This is termed as second generation.

This function decides which value of mean of standard deviation has minimum difference from the original class. If this value is within the threshold then that class (species) will migrate to that habitat.The recalculated HSI after the migration of species is compared with the original HSI of the habitat (that contained training pixels only). If the compared HSI is within the threshold i.e., it varies from -1 to +1 from the original HSI then it means that the habitat is suitable for that species and hence it can migrate to it. Figure 3 is a sample showing the comparison of HSI of training sets' pixels with recalculated HSI after migrating the species. If the recalculated HSI is not within the threshold for any of the original habitat then the particular elementary class contained a mixture of species and it is again partitioned into elementary classes.

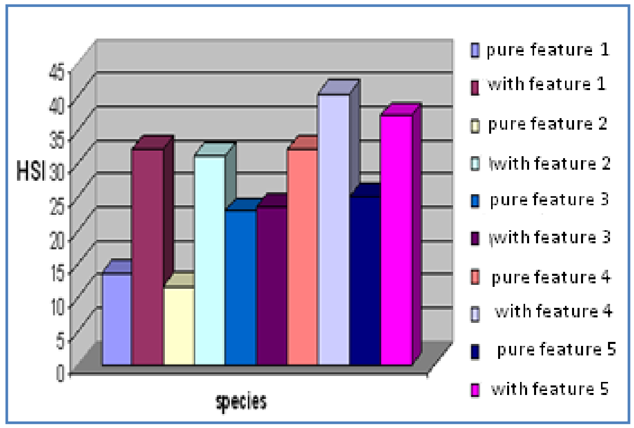

Figure 3: HSI matching in habitats

These classes are migrated into the Universal habitat and considered as unclassified species. These are further used for the next generation/iteration. The checking of all the habitats results in the completion of first generation and then we move towards the second generation for further refinement following the similar process. The maximum number of generations can correspond to the situation when we are left with no more unclassified class (species) in the Universal habitat. The mathematical interpretation of the biogeography based classifier which is based on the concept of information sharing is as represented by figure 4.

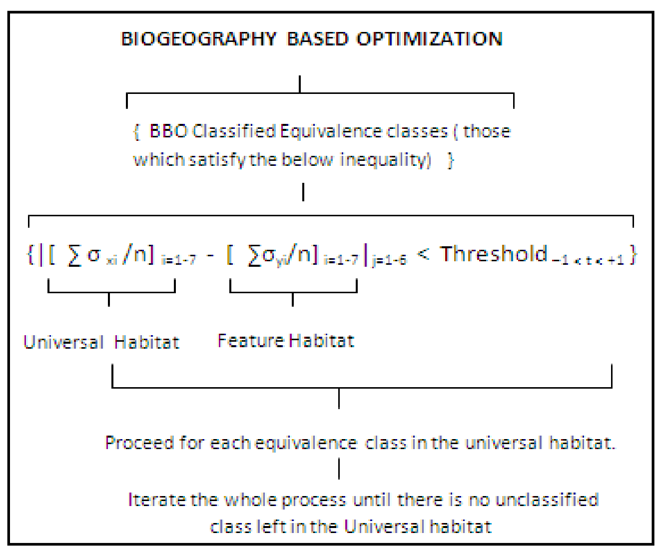

Figure 4: Mathematical formulation of Biogeography based feature elicitator

3.2. Ant Colony Optimization (ACO)

This section discusses the adaptive strategy which is followed to use the concept of information sharing in ACO for elicitation of topographical facets. The major steps are image clustering and heuristic method (HSI) implementation, which form the pillars of the concept of adaptive application of information sharing for terrain features elicitation, are explained next [14].

A widely adopted definition of information sharing through optimal clustering is a partitioning that the intra cluster similarity is minimized while the inter cluster similarity is maximized. For a given problem the pheromone can be set to be proportional to above criteria of the desired. In ACO, we assign each image to a cluster and each ant is giving its own classification solution [13, 14]. The algorithm starts by assigning a pheromone level τ and a heuristic information η to each image. The value for the pheromone level τ assigned to each image is initialized to 1 so that it does not have effect on the probability at the beginning. Heuristic information η ($X\ i\ C\ j$) is obtained from the following formula:

$$\eta_{(X_i,C_j)} = \frac{B}{Sim(X_{i,}C_j)},$$

where X_i represents the feature vector of i^{th} image and C_j is the feature vector representing j^{th} centroid of the cluster. $Sim\ (Xi\ ,C\ j)$ is the similarity between an image X_i and Cj . B is a constant where K is the number of clusters. Assume a number m of ants is chosen for clustering based on the K-Means approach. After all ants have done their classification, the assigned pheromone to this solution is incremented. In order to find global minimum, the pheromone value is updated according to quality of the solution. For updating the pheromone to each clustering the following formula is used:

$$\tau_{(X_{i,}C_j)}(t) = \rho.\tau_{(X_{i,}C_j)}(t-1) + \sum_{a=1}^{m} \Delta\tau_{(X_{i,}C_j)^a}(t),$$

where ρ is the pheromone trail evaporation coefficient (0 <= ρ <= 1) which causes vanishing of the pheromones over the iterations. τ (Xi ,Cj) (t-1) represents the pheromone value from previous iteration. Δτ (Xi ,Cj) $^a(t)$ in the equation above is a new amount of pheromones calculated from all m ants that assign image X_i to j^{th} cluster. This approach of marking solutions by pheromone which is based on the concept of information sharing is proposed as follows:

$$InterSim(a,j) = \sum_{n\neq j}^{K} Sim(C_j, C_n),$$

$$InterSim(a) = \sum_{i\in S_j}^{N_j} \sum_{j=1}^{K} Sim(X_i, C_j),$$

$$\Delta\tau_{(Xi,Cj)^a} = \begin{cases} \frac{N.InterSim(a,j)}{InterSim(a)}, if\ X_i\ belongs\ to\ j^{th}\ cluster \\ 0 \qquad ,otherwise \end{cases}$$

$InterSim(a,\ j)$ represents the sum of the similarities obtained by ant a, between j^{th} centroid and the rest of centroids. $IntraSim\ (a)$ represents the sum of the similarities obtained by ant a, between each image and its centroid. N is the number of images in the dataset and this variable keeps the values of $InterSim(a,\ j)$ and $IntraSim(a)$ in the same order. It becomes clear that the pheromone increases when clusters get more apart and when each cluster has more similar images. Next, the classification performed by each ant is driven by the quality of previous solutions. This is repeated until the best solution for all ants is achieved [14].

3.3. Bee Colony Optimization (BCO)

This section discusses the adaptive strategy we followed to use the concept of information sharing in BCO through FPAB/BBO algorithm [12] for elicitation of topographical facets. The major steps are image clustering and heuristic method (HSI) implementation, which form the pillars of the concept of adaptive application of information sharing for terrain features elicitation, are explained next.

Initially, flowers scattered randomly on 2D discrete grid, which is named as jungle. This jungle can be considered as a matrix of M × M cells. The matrix is toroidal which allows the bees to fly from one end to another easily and there is no initially more than one flower in each cell of jungle. The size of the jungle depends on the number of flowers. We have used a jungle of M × M such m^2= 4n that where n is the total number of flowers (objects) to be clustered.

Initially, the bees are randomly scattered throughout the jungle. We use n/3 bees, where n is the total number of flowers to be clustered. Each garden defined as a collection of 2 or more flowers (or pollens) and for simplicity of algorithm each garden spatially located in a single cell. Consider a garden G with n_g flowers. We define the following parameters:

The compatibility between two flowers in the garden

$$\boxed{C(p_i,p_j) = 1 - D(p_i,p_j)}$$

Where 'D' is normalized Euclidean distance between the attributes of flowers p_i, p_j.
The center of garden G

$$O_{center}(G) = \frac{1}{n_g}\sum_{O_i\in G}^{n} O_i$$

The growth of the pollen in a garden

$$G\ (p_i) = C(\ p_i, O_{center}\ )$$

The flower with minimum growth in a garden G

$$p_{min} = arg\ min\ G(p_i)$$

Where $p_i \epsilon G$.

The main FPAB algorithm [12] is written below:
1. Randomly scatter bees and flowers into the jungle (atmost one flower per cell)
2. Set the initial growth of all flowers to zero

3. Repeat 4, 5, 6 until stopping criteria
4. for each bee do
a) fly the bee in jungle
b) if the bee does not carry any pollen then it possibly picks up a pollen else the bee possibly pollinates.
5. Next bee
6. Natural Selection

Initially, the bees are randomly scattered into the jungle and also randomly pick up or pollinate when they reach a new garden in the jungle. Here, the stopping criterion for the bees is the number of times through the repeat loop.

For elicitation of natural terrain features, we proceed as explained next. Initially homogeneous clusters of image pixels are obtained using FPAB algorithm discussed above. Clusters obtained by honey bees are treated as species in BBO and are put to universal habitats. There are other feature habitats containing the training pixels of the corresponding feature produced by experts. For example, water habitat initially contains pixels of water and standard deviation of all the training pixels of water is calculated in each of seven bands. The HSI is calculated on these training pixels. Each species is taken from the universal habitat and is migrated to each feature habitat one at a time. The HSI of the habitat is recalculated after migrating the species to it. The difference between the original HSI and recalculated HSI is calculated. And if the difference is minimum in some particular feature habitat, species is migrated to that habitat.

3.4. Particle Swarm Optimization (PSO)

This section discusses the adaptive strategy we followed to use the concept of information sharing in PSO for elicitation of topographical facets. The major steps are image clustering and heuristic method (HSI) implementation, which form the pillars of the concept of adaptive application of information sharing for terrain features elicitation, are explained next [15].

Particle swarm classification model treats two dimensional remote sensing images as gravitational field. Each of pixels has different gravitation to particles locating in neighboring of the pixel. The gravitation is searching information in above-mentioned process, but it is updated continually by those particles which has reached the pixel according to classification rules. If the pixel belongs to their types to which particles belong, the gravitation of it to those particles locating in 8-neighborhood around the pixel will be increased by a certain number, otherwise the gravitation will be decreased gradually until to 0. The gravitation can be described using quantitative indicators, and is real number in [0, 1]. The larger the gravitation value is the stronger the gravitation is, otherwise the more weaken the gravitation is.

Particles explore next pixels with certain probability in each time-step, but weight value *W* of next pixels along with searching path are different. At the same time, there is only one particle in each of pixels because operation environment of particles is tow-dimensional images. In order to keep consistency as far as possible with natural behavior of bird swarms, time will be dispersed. Each of particles is permitted to move one and only one step in a time-step. In other words, particles must select one pixel to reach from 8 neighboring pixels. At certain time-step *t*, if the pixel in which the particle locates belongs to congener through distinguished by the particle, the particle will adjusts gravitation of the pixel. Adjustment range is η. In the meanwhile, all of pixels' gravitations will be weakened along with the process of time. The weaken range is κ. According to above conditions, definition of normalization shift probability which particle *p* moves from pixel *k* to pixel *j*:

$$\boxed{p_{ik} = \frac{w(\sigma_i)w(\Delta_i)}{\sum_{j/k} w(\sigma_j)w(\Delta_j)}}$$

In above formula, denominator is a summation formula which represents a weighted sum of gravitations belonging to all of pixels *j* from 8 neighboring pixels of pixel *k*. Δj represents direction change quantity of particle *p* at *t*-1 time. Its value is one of five discrete *W* values. Each of particles will move stochastically with probability *pik* after establishing these parameter values. By this time, each of particles will explore next pixels according to above-mentioned mechanism [15].

4. CONCLUSION AND FUTURE WORK

In this paper, we have demonstrated the fact that the majority of the discovered swarm intelligence techniques are based on the concepts of information sharing. It has been observed that information sharing is an essential part in all swarm based approaches. The particles in a swarm try to solve a problem as a group by using the information contained by their peer mates. Information exchange in swarm-based approaches can take place either directly (as in PSO and BCO) or via the environment. (indirectly as in BBO and ACO). The sharing of information enables swarm particles to be more efficient and to achieve goals that they could not achieve individually. It also helps to intensify the search in the promising regions of the solution space. The information that is shared between individuals in various swarm intelligence techniques can be represented using knowledge representation techniques, which further helps to optimize the problem more efficiently.

Therefore, we illustrate the information sharing concept in each of the major constituent techniques of swarm intelligence that have been used till date namely, Ant Colony Optimization, Particle Swarm Optimization, Biogeography based Optimization and Bee Colony Optimization by means of a terrain understanding application. The paper demonstrates that the information sharing concept can be exploited and utilized in each of these swarm intelligence techniques for solving the problem of natural terrain feature elicitation by means of mathematical formulations and algorithms available. In future, the concept of information sharing can be exploited further to adapt to other applications such as groundwater exploration through case based reasoning using any of the above SI techniques. Also, the above concept can also prove to be useful in military applications for predicting the deployment strategies of enemy troops.

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6. AUTHORS PROFILE

Lavika Goel has done M.E. (Master of Engineering with *Distinction*) in Computer Technology & Applications, Delhi Technological University (formerly Delhi College of Engineering), New Delhi, India, batch 2008-2010 and B-Tech (with Hons.) in Computer Science & Engineering, batch 2004-08 and has always been among the university rank-holders. Holding a corporate world experience, she worked at Oracle India Private Ltd. for six months through campus recruitment and then left it to pursue research in the field of Swarm Intelligence, her interest area. Currently, she is a research scholar working with Defense & Terrain Research Lab at Defense & Research Development Organization (DRDO), Delhi, India.

Dr. Daya Gupta is a professor in the department of computer engineering, Delhi Technological University, New Delhi, India and is currently the head of the department there. She has done M.Sc. (Maths), Post M.Sc. Diploma (Computers Sc.) from IIT, Delhi, Ph.D. She is a senior member of IEEE and a life member of CSI. Her research interests are in the field of requirement engineering, network security, adhoc networks and image classification in remote sensing. She has published several research papers in international journals and conferences and has chaired sessions and delivered invited talks at many national and international conferences.

Dr. V.K. Panchal is an associate director at Defense Terrain & Research Lab, Defense and Research Development Organization (DRDO), New Delhi, India. He is an Associate Member of IEEE (Computer Society) and Life Member of Indian Society of Remote Sensing. He has done Ph.D in Artificial Intelligence and is currently working as Scientist 'G' at DRDO, Delhi. He has chaired sessions & delivered invited talks at many national & international conferences. His research interests are in the synthesis of terrain understanding model based on incomplete information set using bio-inspired intelligence and remote sensing.