# Image Restoration using BBO and ACO

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***Abstract***— Digital image processing plays a vital role in the analysis and interpretation of remotely sensed data. Image restorations techniques help in improving the visibility of any portion or feature of the image suppress sing the information in other portions or features. Image restoration improves the perceptibility of objects in the scene by restoration the brightness difference between objects and their backgrounds. Image restoration is typically performed as a contrast stretch followed by a tonal enhancement, although these could both be performed in one step. Applications of the Ant Colony Optimization (ACO) to solve image processing problem with a reference to a new automatic restoration technique based on real-coded particle ant colony is proposed in this paper. The restoration process is a non-linear optimization problem with several constraints. The objective of the proposed ACO is to maximize an objective fitness criterion in order to enhance the contrast and detail in an image by adapting the parameters of a novel extension to a local enhancement technique. In this paper enhancement occurs on the basis for the development of a new field: biogeography-based optimization (BBO). We discuss natural biogeography and its mathematics, and then discuss how it can be used to solve optimization problems. We see that BBO has features in common with other biology-based optimization methods, such as GAs and particle swarm optimization (PSO). This makes BBO applicable to many of the same types of problems that GAs and PSO are used for, namely, high-restoration problems with multiple local optima.

## I. INTRODUCTION

Optimization is way to modify any design or decision as efficient as possible. There are many optimization techniques which have been used in order to extract best solution. Restoration of various medical images is of great importance these days. Medical images include images like mammographic images, X-Ray images, ultrasound images and many more. X-ray imaging is a popular and most commonly used method for diagnosing the internal bone structures of the body. It is used to find orthopaedic damage, tumours, pneumonias, foreign objects, etc. Unfortunately, X-Ray images appear low image quality caused by fairly low spatial resolution and the presence of noise. X-Ray images also suffer from noise and blur hence they also need restoration in order to remove blur and noise. Hence restoration of X-Ray images is very challenging. We will first degrade the original image using Motion Blur then restore using BID-ACO. Particle Swarm optimization (PSO), Ant Colony Optimization (ACO), Genetic algorithm (GA) are some of the examples of optimization technique. In this paper, we use biogeography based optimization technique is used. Ant Colony Optimization: The ant colony optimization algorithm (ACO) is a probabilistic technique for solving many problems which can be reduced to finding good paths through graphs. Although real ants are blind, they are capable of finding shortest path from food source to their nest by exploiting a liquid substance, called pheromone, which they release on the transit route. This algorithm is a member of ant colony algorithms family, in swarm intelligence methods, and it constitutes some met heuristic optimizations. Ant Colony Optimization (ACO) is a population-based, general search technique for the solution of complex continuous problems which is inspired by the pheromone track laying behaviour of real ant colonies. The behaviour of ant is intimidated in artificial ant colonies for the search of estimated solutions to discrete optimization problems, to continuous optimization problems, and to important problems in telecommunications, such as routing and load balancing. Initially proposed by Marco Dorigo in 1992 in his PhD thesis, the first algorithm was aiming to search for an optimal path in a graph, based on the behaviour of ants looking for a path between their colony and a source of food. The ant colony optimization (ACO) metaheuristic a colony of artificial ants assists in finding good solutions to difficult discrete optimization problems. The choice is to allocate the computational resources to a set of relatively simple agents (artificial ants) that communicate indirectly. Good solutions are an emergent property of the agents' cooperative interaction. The original idea has since diversified to solve a wider class of numerical problems, and as a result, several problems have emerged, drawing on various aspects of the behaviour of ants. The main underlying idea, loosely inspired by the behaviour of real ants, is that of a parallel search over several constructive computational threads based on local problem data and on a dynamic memory structure containing information on the quality of previously obtained result. The collective behaviour emerging from the interaction of the different search threads has proved effective in solving combinatorial optimization (CO) problems. The developed AS strategy attempts to simulate behaviour of real ants with the addition of several artificial characteristics: visibility, memory, and discrete time to resolve many complex problems successfully such as the travelling salesman problem (TSP), vehicle routing problem (VRP), and best path planning, Even though many changes have been applied to the ACO algorithms during the past years, their fundamental ant behavioural mechanism that is positive feedback process demonstrated by a colony of ants is still the same. Ant's algorithm has also plenty of networking applications such as in communication networks and electrical distribution networks.

## II. OVERVIEW OF DIFFERENT TECHNIQUE TO RESTROE IMAGE

Image restoration is the improvement of digital image quality (wanted e.g. for visual inspection or for machine analysis) without knowledge about the source of degradation. The source of degradation is known one calls the process image restoration. The principal objective of image restoration is to process a given image so that the result is more suitable than the original image for a specific application. This accentuates or sharpens image features such as edges; boundaries; or contrast to make a graphic display more helpful for display and analysis. The restoration doesn't increase the inherent information content of the data; but it increases the dynamic range of the chosen features so that they can be detected easily. The greatest difficulty in image restoration is quantifying the criterion for restoration and, therefore, a large number of image restoration techniques are empirical and require interactive procedures to obtain satisfactory results. Image restoration methods can be based on either spatial or frequency domain techniques. In this paper, survey different algorithms for the Image Restoration (enhance) purpose; these are shown below in figure

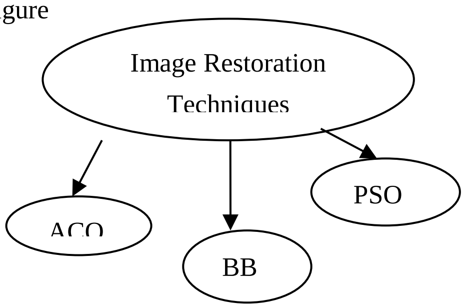


Fig.1: Image Restoration Techniques

These techniques which shown in figure1 discuss as follow in paper.

## III. ANT COLONY OPTIMIZATION

ACO has been recently developed as a population based Meta heuristic that has been successfully applied to several NP-hard combinatorial problems. The ACO is the one of the most recent techniques for approximate optimization methods. The main idea is that it is indirect local communication among the individuals of a population of artificial ants. The core of ant's behaviour is the communication between the ants by means of chemical pheromone trails, which enables them to find shortest paths between their nest and food sources. The role of pheromone is to guide the other ants towards the target points. This behaviour of real ant colonies exploited. The ACO is consisted of three main phases; initialization, pheromone update and solution phase. All of these phases build a complete search to the global optimum. At the beginning of the first iteration, all ants search randomly to the best solution of a given problem within the feasible solution space, and old ant colony is created at initialization phase. After that, quantity of Pheromone is updated. In the solution phase, new ant colony is created based on the best solution from the old ant colony. Then, the best solutions of two colonies are compared. At the end of the first iteration, feasible solution space is reduced by a vector that guides the bounds of search space during the ACO application. Optimum solution is then searched in the reduced search space during the algorithm progress. The ACO reaches to the global optimum as ants find their routes in the limited space. A simple ACO Algorithm consists of the steps: The algorithm starts with ant colony being placed randomly on the search space. The main steps include,

- Initialize ant colony.
- Initialize the pheromone trail.
- Evaluate fitness of the each ant in the colony.
- Determine the best optimum solution among all ants in the colony.
- Update Pheromone trail.
- Determine the search direction for further search.
- Construct new solution using obtained best optimum solution.
- Generate new colony

In this section we discuss the Ant Colony optimization algorithm used for chain construction. ACO makes sure that none of the inter-nodal distances becomes extremely large during chain construction i.e. they never exceed a threshold value. Ant Colony Optimization is inspired by the behaviour of real ants searching for food. The main objective of ACO is to utilize both local information (visibility) as well as information about good solutions obtained in the past (pheromone), when constructing new solutions. To apply ant algorithm in our problem, we place ants arbitrarily on the nodes. Each ant is a simple agent with certain memory attributed. According to a probability, an ant chooses the next node into which it has to move into. This probability is a function of inter-nodal distance and pheromone deposited upon the link. Every ant has a taboo table recording nodes which the ant has already accessed. The Taboo table forbids the ant to move into previously visited nodes. At the end of travelling an ant deposits pheromone on the paths it has travelled through. Based on the information collected an ant determines an ant's choice of node from its neighbourhood. In the proposed ACO Algorithm two ants are used. One ant which is created at Source S and moves to destination D. The other ant, which is created at Destination and follows the path from source to destination and updates the route table.

$$T(m,n) = \frac{r(m,n)}{\sum_{s \in Nm} r(m,s)} \text{ if } s \in Nm \tag{1.1}$$

Where Nm is Neighbour Node r (m,n) is pheromone strength

$$\sum_{s \in Nm} T(m,n) = 1 \tag{1.2}$$

When node S sends a packet to destination node D Node searches the destination route in the routing table. If it is not available in the routing table, it creates a forward ant with source address and broadcasts to all adjacent nodes. When an intermediate node m receives the forward ant it checks destination address of forward ant, if destination address is not same node m adds own address and time forward ant arrived to m, node m adds the source address as destination address for routing backward ant, into routing table and computes pheromone value according to formulae shown above . Hop count is also updated. Node m broadcasts forward ant to neighbour again, if did not receive the route of destination. When node m receives duplicate forward ant i.e., with same sequence number and source address, the previous steps are followed. If sequence number is less than or equal to max sequence number and route record of forward ant includes address of present node, then the forward ant is discarded. Otherwise node updates the max sequence number by new value and executes the previous steps. When destination of forward ant is same as that of m, route is discovered. Forward ant is discarded after retrieving relevant information from forward ant, and backward ant is sent on to the path followed by forward ant. Again the pheromone table is updated as per backward ant. When backward ant reaches to the source S all the pheromone tables are updated. When there is congestion at node m, node m will retrace the path of forward ant to inform to source S to change route. Pheromone value is changed from source and same value is updated in routing table, so that congested path is not further loaded. When all the routes fail, source S will initiate a new route request again. When there is error in the node, mainly due to change in location of mobile node. The pheromone value is made to 0, so that route is not followed by the multicast node.

In this way the entire chain is constructed. The chain is reconstructed using ACO when a node dies, but by bypassing it and by following all the above mentioned facts.

## IV. BIOGEOGRAPHIC BASED OPTIMIZATION

Biogeography Based Optimization is method which is improved version of genetic algorithm. Genetic algorithm analyzes genetic power of species or human. Type of species whose specimens are taken for genetic calculation is defined by Biogeography Based optimization (BBO).Biogeography Based optimization technique is motivated from the word biogeography. Biogeography is the study of plants and animals. The groups of birds or fishes are moving from one habitat to other depending on various factors like food resources, climatic conditions etc. This is basic idea behind the origin of Biogeography Based optimization technique .By using this technique the solution of any particular problem can be measured. Biogeography Based optimization technique is based on information sharing by species migration. The sharing of features among the habitat is called migration. Migration results in the modification of existing individual. Biogeography is the study of the geographical distribution of biological organisms. Biogeography based Optimization (BBO) is an application of biogeography to optimization problems. It is modelled on the immigration and emigration of species between the islands. BBO was first presented in December 2008 by D. Simon. A supervised classification of remote sensing image based on BBO is proposed. In this first random clusters of the image are formed using rough set theory. Then each cluster is put in the universal habitat, considering each cluster as a species of universal habitat. The feature habitats initially contain training pixels and Habitat Suitability Index (HSI) is calculated on these training pixels. Then each of the species is migrated to feature habitat one by one and HSI of the habitat is recalculated after migration. A given species is absorbed (and hence it belongs) to that feature habitat where it makes minimum variation in HSI after migration. The good solution is considered to have high HSI value and poor solution have low value. Let the size of habitat be N.

$$H = [SIV1, SIV2, SIV3 \ldots SIVM] \quad (2.1)$$

Where M is the number of feature to involve for optimal solution. Segmentation is the process of dividing the image into set of pixels having homogeneous region. It is used to locate boundaries or objects. Close part of image is considered as object [2]. In Migration, pixels having similar intensity, color or characteristics are migrated and grouped together when biogeography based optimization applied to image .The initial seed is selected randomly and find whether the pixels neighbour added or not. In BBO each solution learns from their neighbouring pixel. Solution changes through migration from other solution. HSI contain pixels that have similar properties and LSI contain the pixel having different properties. Select the threshold value and perform thresholding. The simplest is based on a clip-level or a threshold value to turn a gray-scale image into a binary image. That binary image contains all the information about shape of object of interest. Thresholding is iterative process consists of following steps:

1) Step-1: An initial threshold (T) is chosen; this can be done randomly or according to any other method desired.
2) Step-2: The image is segmented into object and background pixels as described above, creating two sets:
$G1=\{f(m,n):f(m,n)>T\}$(object pixels)
$G2=\{f(m,n):f(m,n)\ T\}$ (background pixels)
Where f (m, n) is the value of the pixel located in the mth column, nth row.
3) Step-3: An initial threshold (T) is chosen; this can be done randomly or according to any other method desired. The average of each set is computed. M1 is average of G1 and M2 average of G2.
4) Step-4: A new threshold is created that is the average of M1 and M2.
New threshold $T=(M1 + M2)/2$
5) Step-5: Go back to step two, now using the new threshold computed in step four, keep repeating until the new threshold matches the one before it.

By using thresholding, pixels having similar properties or belongs to HSI are grouped together and pixels having different properties or LSI pixels belongs some other region. So after this migration process object pixels are isolated from background pixels. As we started we select a seed using some set of predefined criteria. After selecting examine neighbour pixels of seed points and calculate MSE color distance between pixels. According to the BBO approach make three islands HSI and LSI.HSI (highly suitability index) that contain pixels which have more similar properties. Low suitability index (LSI) that contain pixels which contain pixels that not so familiar. HSI tend to have a large number of species, while those LSI have a small number of species. Then we select threshold. If our calculated distance less than threshold then its migrate to other region, otherwise its make its own region

## V. PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization (PSO) is a swarm intelligence technique developed by Dr. Eberhart and Dr. Kennedy in 1995. In PSO, the swarm consists of particles which move around the solution space of the problem. These particles search for the optimal solution of the problem in the predefined solution space till the convergence is achieved. The search heuristics in PSO is iteratively adjusted guided by a fitness function defined in terms of maximizing class separation. The proposed algorithm was found to generate excellent recognition results with less selected features. The main contribution of this work is:

Formulation of a new feature selection algorithm for face recognition based on the binary PSO algorithm. The algorithm is applied DWT feature vectors and is used to search for the optimal feature subset to increase recognition rate and class separation. Evaluation of the proposed algorithm using the ORL face database and comparing its performance with a PCA, ICA LDA feature selection algorithm and various FR algorithms found in the literature.

*A.* PSO algorithm:

- Initialize the particle position by assigning location p = (p0, p1…., pN) and velocities v = (v0, v1, …, vN).
- Determine the fitness value of all the particles: f (p) = (f (p0), f (p1)… f (pN)).
- Evaluate the location where each individual has the highest fitness value so far: p= ($p0^{best}$, p1best… pNbest).
- Evaluate the global fitness value which is best of all $p^{best}$: G (p) = max (f (p)).
- The particle velocity is updated based on the $p^{best}$ and $g^{best}$.
- $v_i$ new = v1 + c1 × rand ( ) × ($p_i^{best}$ - pi) + c2 × rand ( ) × ($p_g^{best}$ - pi)
- For 1 < i< N. (1)
- Where c1 and c2 are constants known as acceleration coefficients and rand () are two separately generated uniformly distributed random numbers in the range [0, 1].
- Update the particle location by: $p_i^{new}$ = pi + $v_i^{new}$ for 1 < i < N.
- Terminate if maximum number of iterations is attained or minimum error criteria is met.

*B.* Binary PSO:

For binary discrete search space, Kennedy and Eberhart have adapted the PSO to search in binary spaces by applying a sigmoid transformation to the velocity component in the equation to squash the velocities into a range [0,1] and force the component values of the positions of the particles to be 0's or 1's. The sigmoid expression is given by:

$$sigmoid\left(p_{id}^{k}\right) = \frac{1}{1-e^{-v_{id}^{k}}} \quad (3.1)$$

$$\left(p_{id}^{k}\right) = \begin{cases} 1 & if\ rand(\ \ ) < sigmoid\left(p_{id}^{k}\right) \\ 0 & otherwise \end{cases} \quad (3.2)$$

*C.* Feature Extraction

In pattern recognition and in image processing, feature extraction is a special form of dimensionality reduction. When the input data to an algorithm is too large to be processed and it is suspected to be notoriously redundant (e.g. the same measurement in both feet and meters) then the input data will be transformed into a reduced representation set of features (also named features vector). Transforming the input data into the set of features is called feature extraction. If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input. The first step in any face recognition system is the extraction of the feature matrix. A typical feature extraction algorithm tends to build a computational model through some linear or nonlinear transform of the data so that the extracted feature is as representative as possible.

*D.* Feature selection using binary PSO

Feature selection is performed to reduce the dimensionality of facial image so that the features extracted are as representative as possible. Method employed here is Binary PSO. Consider a database of L subjects or classes, each class W1, W2, W3… WL with N1, N2, N3,…NL number of samples. Let M1, M2, M3... ML is the individual class mean and M0 be mean of feature vector. Fitness function is defined so as to increase the class separation equation. By minimizing the fitness function, class separation is increased. For iteration the most important features are selected. Binary value of 1 of its position implies that the feature is selected as a distinguishing feature for the succeeding iterations and if the position value is 0 the feature is not selected.

## VI. LITERATURE SURVEY

Jimg Tian et.al finds that Image restoration is the process of clearing the degraded image to obtain the original image. The main focus of the work is to restore the blurred X-Ray image using Blind Image Restoration. This is much important part of image restoration to recover image without the knowledge of the reason of its degradation. In the edges of the blurred X-Ray image; the ringing effect can be detected using Ant Colony Optimization method and then it can be removed before restoration process. And estimate is done about the unknown degradation function and using that an estimate of the original X-Ray image is produced. Ant colony Optimization (ACO) is a nature inspired optimization algorithm that is motivated by the natural foraging behaviour of ant species.

C. Naga Raju et. al. discuss about Images can be processed by optical; photographic; and electronic means but image processing using digital computers is the most common method because digital methods are fast; flexible; and precise. Figure processing modifies pictures to improve them by image restoration technique and extract information and change their structure. The common problems in an image are noise and blur. Image is restored by removing blurring and noise. To improve quality of restored image particle swarm optimization; ant colony optimization and biogeography based optimization techniques are used. This paper's technique of biogeography based optimization is applied for image restoration.

K.Uma et. al. image compression (FIC) is based on the partitioned iterated function system (PIFS) which utilizes the self-similarity property in the image to achieve the purpose of compression; the linear regression technique from robust statistics is embedded into the encoding procedure of the fractal image compression Another drawback of FIC is the poor retrieved image qualities when compressing corrupted images; the fractal figure compression scheme should be insensitive to those noises presented in the corrupted image. It leads to a new concept of robust fractal image compression. Then FIC is one of our attempts toward the design of robust fractal image compression. Thus main disadvantage of FIC is the high computational cost. And to overcome this drawback; the technique described here utilizes the optimization techniques like GA; ACO and PSO which greatly decreases the search space for finding the self similarities in the given image.

## VII. CONCLUSIONS

This research indicates directions for further research. The proposed framework can be analysed in terms of feasibility and acceptance in the industry. Trying to improve the performance of existing methods and introducing the new methods for Image restoration based on today's software project requirements can be future works in this area. So the research is on the way to combine different techniques for calculating the best estimate. According to the findings of the research, it is purposed that the hybridization of ACO and BBO technique can be used to find the best method for image Restoration. Different Algorithm on Image Restoration has been proposed previously but there have been always need for better results or Restoration of Image. The existing Image Restoration uses algorithm which is poor in quality. The existing Image Restoration results are more prone to noise and less accurate. The existing performance of Image Restoration System needs further enhancement.

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