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Impact of Metaheuristic Nature Inspired Algorithms on Image Enhancement

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Abstract: **The paper presents the analysis of two metaheuristic nature inspired algorithms which are chosen for the purpose of enhancement of gray level image. Firstly, the particle swarm optimization (PSO) algorithm is investigated and then the ant colony optimization (ACO) algorithm. The input image is transformed in order to maximize the information content of the enhanced image. The parameters of the transformed image are then evaluated by the fitness function. The iterative working of the algorithms give the optimum fitness value along with the optimal values for the parameters such as the number of iterations, population size, edge intensities and edge pixels. Finally, a comparative analysis of PSO and ACO has been presented on the basis of the chosen parameters. The analysis has revealed that ACO provides better performance than PSO in terms of computational time, edge pixel detection and edge intensities in an image. However, PSO has its own advantages as it takes exploration as well as exploitation into consideration while finding the optimal solution.**

Keywords: **Metaheuristic, particle swarm optimization, entropy, histogram equalization, ant colony optimization.**

I. INTRODUCTION

The recent advancements in science and technology have brought with them the solutions to almost every problem under the sky. The goal is to find the optimal solution for such problems. Optimization can be defined as the practice of selecting the most efficient and feasible solution from the plethora of solutions [1]. Nature has acted as an inspiration to solve the real world optimization problems. In addition to the traditional optimization techniques, many contemporary algorithms have been developed that are inspired from nature. These algorithms are classified into swarm intelligence (SI) based, bio inspired based and physics- chemistry based algorithms. The classical Particle Swarm Optimization (PSO), Ant colony optimization (ACO), firefly algorithm etc. come under the category of SI based algorithms. The SI algorithms are part of bio-inspired algorithms hence, there are algorithms that are bio inspired but not swarm intelligence based such as differential Evolution, flower algorithm etc. [2] There are certain algorithms that are not bio inspired but are based on physics- chemistry such as spiral optimization, black hole, gravitational search, harmony search, simulated annealing etc. [3].

The problem of optimization is very important even in the field of imagery. Nowadays, digital images are playing a pertinent role to acquire, store and communicate information among people, businesses, corporations and security outfits. Hence, the dire need is to ensure the integrity of digital images which are particularly useful for forensics and various other security purposes [4]. Although, numerous attempts have been made to enhance the gray images (GI). However, many techniques are fully manual or partially automated [5]. Moreover, the automated techniques which are present depend only on the global information of the image without considering the local details [6]. The techniques for image enhancement can be broadly classified into four main categories: point operation, transformation, spatial operation and pseudo coloring [7]. There are different image enhancement operators: sobel, canny and prewitt.[8] Firstly, different images are compared on the basis of three chosen image enhancement operators i.e, sobel, canny and prewitt operators. Then the particle swarm optimization technique and ant colony optimization algorithm has been applied on the input image based on certain parameter settings.

II. PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization algorithm is a heuristic algorithm that can be applied to nonlinear and non-continuous optimization problems. It was developed in 1995 by Kennedy and Eberhart [8]. It is a population based stochastic optimization technique and is based on the simulation of the social behavior of birds within a flock. In PSO, the individual particles are considered to be the solutions. These particles are passed through the hyper dimensional search space. On each iteration, there are specifically two updates that take place[9]:

- Velocity update: It depends upon the difference between particle's best position (*pbest*) and current position of particle. Also, it depends upon the difference between swarm's best position (*gbest*) and current position as shown in eq. (1).
- Position update: It depends upon previous position and current velocity. The position of any particle is n dimensional.

In PSO, each potential solution is assigned a randomized velocity and each particle adjusts its flying according to its own flying experience besides the swarm's flying experience [10]. The velocity update equation is given by:

$$V_i^{t+1} = w.*V_i^t + C_2.*\, r_1^t\, [pbest_i^t - X_i^t] + C_2.*r_1^t[\text{gbest} - X_i^t]$$
$$X_i^{t+1} = X_i^t + V_i^{t+1} \qquad (1)$$

Where, V_i is the velocity of each particle at iteration t which depends upon the difference between *pbest* and current position of each particle, also it depends upon the difference between the *gbest* and current position of each particle. C_1 and C_2 are the acceleration coefficients. *pbest* is the particle's best solution and gbest is the swarm's best solution. W is the inertia coefficient. X_i is the position of i^{th} particle at iteration t.

III. ANT COLONY OPTIMIZATION

Ant Colony Optimization is a population based metaheuristic that was proposed by Dorigo and Gamberdella in early 1990's and now has been successfully applied to several NP-hard combinational problems [11]. The ACO is a recent technique for approximating discrete optimization problems. It mimics the foraging behavior of real ants, especially their ability to find the shortest path between the food source and their colonies. The ants deposit pheromone on their trail paths they traverse which helps them to perform indirect communication (also termed as Stigmergy) [12].

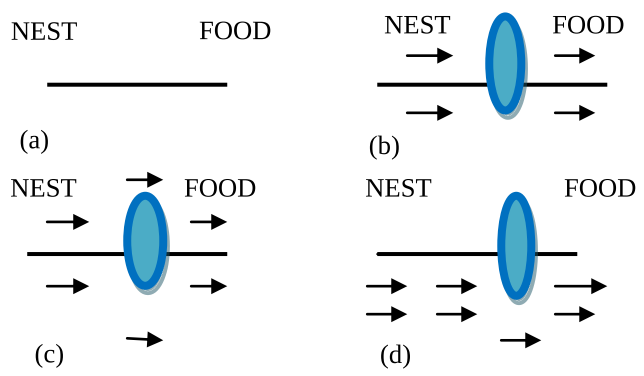

Fig 1: The demonstration of the shortest path finding capability of ants' between the nest (ant colonies) and the food source. (a) No obstacle between the path, (b) Obstacle is placed between the path, (c) Ants on the path determining the optimal path, (d) Ants has discovered the optimal path.

The role of pheromone is to guide other ants to reach to the particular destination point. This is explained in the Fig. 1. The ACO consists of three main phases: initialization of the ants' parameters, pheromone update and the solution

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phase. All the three phases build a complete search to the global optimal solution. In the first iteration, all the ants randomly search in the feasible solution space for the best solution of a given problem. In the next phase, quantity of pheromone is updated and thus using the best solution from the previous results, new ant colony solution is also updated. At last, both the results are compared and feasible solution space is reduced by a vector. Now the ACO reaches the global optimal solution and ants find their routes in the limited search space [13].

In ACO algorithm, parameters are initialized accordingly. Then, initialize the random pixels as ants and update them one after another. Evaluate the pheromone trail for calculating the fitness of every ant in the colony is calculated by the sum of intensities of the edges in an enhanced image. The best fitness value is calculated and the pheromone trails are updated for determining the corresponding search space for ants. The new solution is constructed using the previous best optimal solution and new ant will be generated by again initializing the new pheromone trail and the process continues as shown in algorithm 2.

Hence, the updating of pheromone matrix with every iteration leads to the formulation of new images, thus giving optimum result at the end of iterations having the maximized value of parameters.

The objective of this research is to compare two selected nature inspired algorithms on the basis of selected parameters for the problem of image enhancement. The standard edge detection operators have been compared and the chosen NIAs have been implemented along with them.

IV. METHODOLOGY

In this paper, various NIA algorithms have been analyzed and different image enhancement operators are identified. It has been tried to implement these techniques over the grey scale images to clear comparative results. The transformation of image is the first step in the whole methodology. Let I be the input image to be transformed having the dimension ($M*N$). The input image is converted to grey scale image G, having the same dimension $M*N$. The local mean, global mean and local standard deviation (σ) are calculated for the grey scale image G. These parameters are further used in image transformation and evaluation step.

A. IMAGE TRANSFORMATION AND EVALUATION

An image transformation in spatial domain changes the intensity value of a gray image pixel to a different value. The objective is to maximize the information content of the enhanced image. [14] The transformation function uses the local and global information of the image as shown in eq. (2):

$$F_{i,j} = T(G_{i,j}) \quad \forall i \in M;\ j \in N$$
$$= (k * \mu_G / \sigma_{i,j} + b) * (G_{i,j} - c \times \mu_{i,j}) + (\mu_{i,j})^a \tag{2}$$

where, T is the transformation function applied on the input image G and transforming every pixel i, j of the input image. a, b, c and k are the parameters of the enhanced kernels to be optimized, having values as, $0.5 < k < 1.5;\ 0 \leq a \leq 2;\ \mu_G < b < 0.5$ and $0 \leq c \leq 1$. Thus we have a transformed image by calculating $F_{i,j}$ and consecutively number of edges, $N_e \in F_{i,j}$ will be computed using sobel operator. The sobel operator produces an image of edges $E_{i,j}$ which describes the edge pixels in $F_{i,j}$ and zeros at corresponding pixel values. Thus, the total number of edges in $E_{i,j}$ is computed as shown in eq. (3):

$$N_e = \sum_{i=1}^{M} \sum_{j=1}^{N} E_{ij} \tag{3}$$

The intensity of the pixels $\xi_{i,j}$ is calculated as shown in eq. (4):

$$\xi i, j = E_{ij} \bullet F_{ij} \tag{4}$$

Where, ● denotes the element wise multiplication. Therefore, total intensity of $F_{i,j}$ is given in eq. (5):

$$\Phi = \sum_{i=1}^{M} \sum_{j=1}^{N} \xi i, j \tag{5}$$

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The fitness function to evaluate the enhancement of an image is given as in eq. (6). The eq. takes into consideration the number of edge pixels, entropy of the image and sum of edge intensities[13]:

$$Z = log(log(\Phi)) \times (N_e/(M*N)) \times exp(H(F_{i,j})) \quad (6)$$

Where, $H(F_{i,j})$ is the entropy of the enhanced image $F_{i,j}$, N_e is the number of edge pixels, $M*N$ is the size of the image and Z is the fitness value of the image that is the optimum value at which the parameters a, b, c and k give the maximum results within the prescribed range.

A. PSEUDOCODE FOR PSO

The PSO algorithm using the flock behavior of birds is applied here to find the optimum value of *a*, *b*, *c* and *k* mentioned in eq. (1), for the sharpened enhanced image. Initially, the transformation parameters are initialized randomly. The particles of the swarm are considered to be the solutions which are initialized randomly [15]. The pseudo code of PSO is shown in algorithm (1)

For each particle, n = 1 to P, do
Initialise each particle
Compute the fitness value of each particle, n using (5), after transformation using (1)
Compare the pbest(t) and pbest(t+1), and do
If pbest(t+1) > pbest(t)
Then, pbest(t+1) is made the current best value of the particles.
Return to 1, and do for all P
Obtain the gbest at t+1
If gbest(t+1) > gbest(t)
Then, gbest(t+1) is made the current global at t+1.
Thus, compute the next value of the velocity and the particles using (6)
Return to 1, until P.
Continue while maximum iterations or minimum error criteria is not attained

Algorithm 1: Pseudo code for PSO used for image enhancement

Each particle uses the fitness value obtained from eq. (5) to find the pbest (personal best solution for each particle) and gbest (global best solution for each particle) solution. That is, the property of PSO to perform exploration as well as exploitation helps in searching for the global best and local best solution [15]. The successive steps are shown in algorithm 1. Hence at each iteration, fitness value gives new gbest and pbest. By using these values, new velocity and position of each particle is calculated to update the new solution with the existing one. As the process completes, the enhanced image is created by the gbest particle which provides the maximum fitness value. Though at times PSO tends to get stuck in local optima but its exploitative as well as explorative behavior gives optimized results.

B. PSEUDOCODE FOR ACO

The ACO algorithm mimics the foraging behavior of real ants and is applied here to find the optimum value of the given parameters to enhance the image [16]. The subsequent steps of ACO are shown in algorithm 2.

while termination conditions met do
Schedule activities
procedure Ant colony optimization
Set initialize parameters, pheromone trails
while(termination condition not met)
do
Construct Ant Solution
Update Pheromone Trails
Daemon Actions
end
end Schedule activities
end while

Algorithm 2: Pseudo code for ACO used for image enhancement

The ACO algorithm aims to search for an optimal path in the trail path, based on the behavior of ants. After initializing the parameters and the pheromone trails, ant solution is created. Once the ant solution is created, ants evaluate their solution and concurrently update their pheromone trails.

V. RESULTS

The above algorithms have been implemented and experimented. The result shows that the parameters to be optimized i.e., *a*, *b*, *c* & *k* as shown in eq. (4) give optimum results as

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explained earlier, if their values are selected in the prescribed range i.e., *a ϵ [0,1.5], b ϵ [0, D/2], c ϵ[0,1] and k ϵ [0.5,1.5]* where *D* is the global mean of the input image.

For experimental analysis many images have been observed but the results are shown for the selected few images. The results of these selected images are shown in Fig. 2. The parameters taken for comparison includes sum of pixel intensities *(s)*, number of edge pixels *(n)* and computation time *(t)* for distinguishing between ACO and PSO. The resultant output is shown in Table 1. However only human interpretation is required to distinguish between images produced from sobel, canny and prewitt operator as shown in Fig 2.

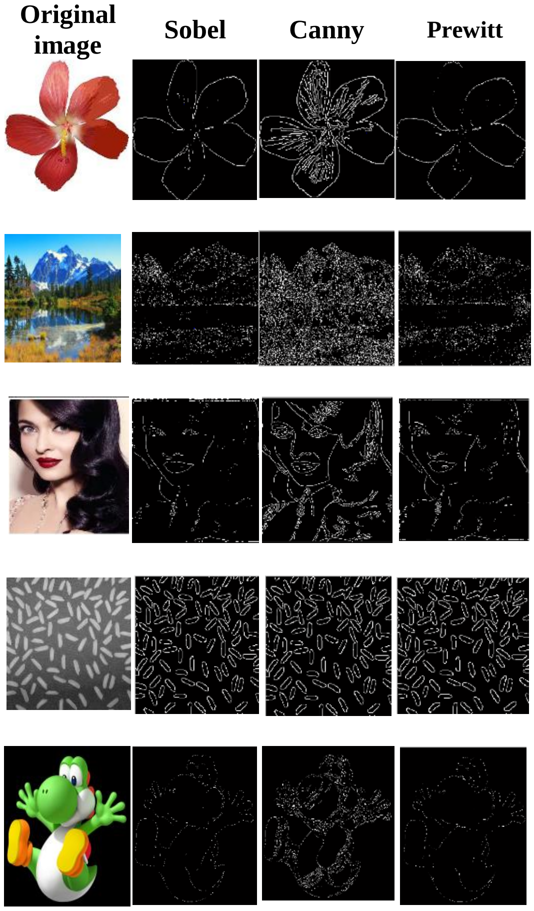

Fig 2: Different outputs obtained in images by using sobel, canny and prewitt operator.

The initialization values of the parameters of PSO and ACO are shown in Table 1 and Table 2 respectively. These values have been kept constant throughout the process.

Table 1: Values of parameters of PSO

Parameters	Values
it	10
P	10
W	[0, 2]
C1 & C2	0.6

Where, *it* is the number of iterations, *P* is the number of particles i.e. the swarm size or the population size, W ∈ [0-2] is the inertia factor . C1 and C2 are the cognitive and social constants respectively.

Table 2: Values of parameters of ACO

Parameters	Values
MaxIt	10
nAnt	10
A	1
β	1.5
P	0.5
Q	1
τ	0

Where, *MaxIt* is the maximum number of iterations used in the ACO algorithm, *nAnt* is the total population size of ants, $A \in [0, 2]$ is the pheromone exponential rate, $\beta \in [0, 2]$ is the Heuristic exponential rate, the parameter $P \in [0, 1]$ is a parameter that regulates the rate at which the pheromone evaporates, Q is used for controlling the level of evaporation of pheromone and *tau* is the initial pheromone. The experimental results are shown in table 3, where comparative analysis has been done between ACO and PSO. The sum of edge pixel intensities are more in PSO generated images as it makes use of its exploitative and explorative behavior.

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Table 3: Comparative analysis of ACO and PSO

Para m-eters	Sum of pixel intensities(s)		Number of edge pixels(n)		Computation time(t)	
Img	**ACO**	**PSO**	**ACO**	**PSO**	**ACO**	**PSO**
3(a)	11025	10462	11025	4595	6.289	13.37
3(e)	24478	63892	22030	37820	11.920	15.95
3(i)	2235	85477	20115	8340	5.8395	11.41
3(m)	3234	5567	23145	1233	6.876	12.78
3(e)	7678	3343	2344	4412	7.456	13.33

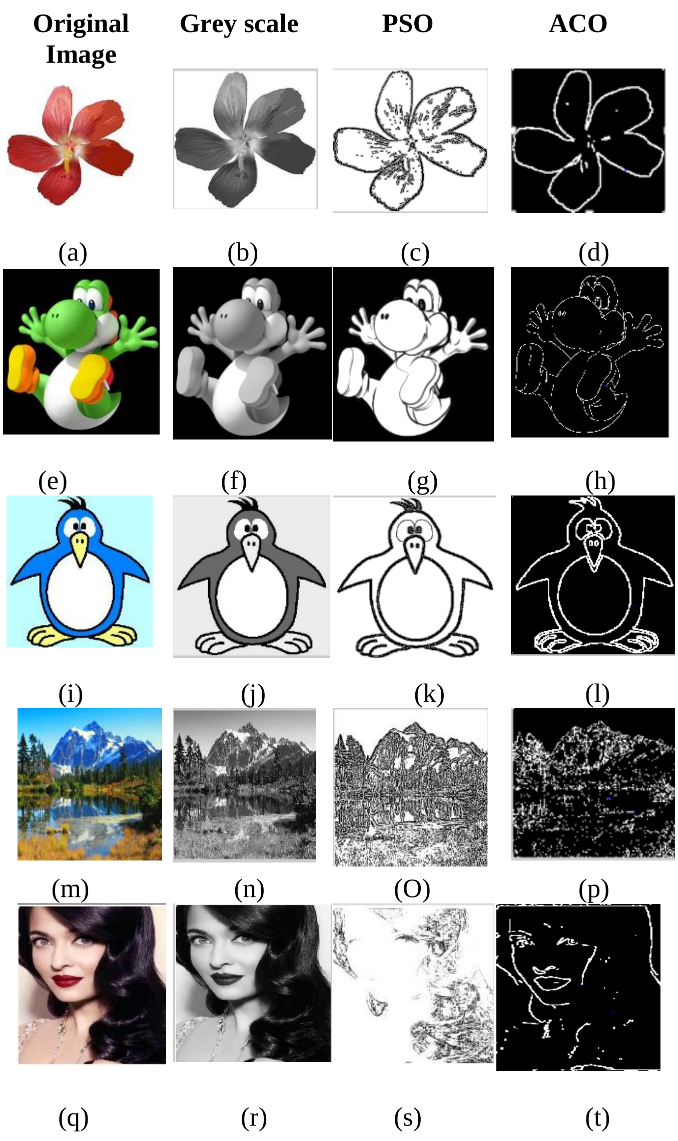

Fig 3: Edge detected images using application of PSO and ACO function.

However, ACO gives higher number of edge pixels in images leading to sharpened detection of edges. Also, computation time is more in ACO than PSO. The comparative analyses of both the algorithms are shown in table 3.

It has been given in Fig. 3(c, d), 3(g, h), 3(k, l), 3(o, p) and 3(s, t) shows the sharpened detected edges by PSO and ACO algorithm. Both the algorithms have been applied with the sobel operator to give much sharpened edges in terms of number of edge pixels, sum of pixel intensities and entropy as shown in Fig 3:

At last, it is concluded that PSO works better than ACO in case of providing sum of pixel intensities. Also it should be noted that ACO and PSO are statistical in nature, hence, they often give different results on different runs. While calculating the number of edge pixels ACO works better. The results are shown in Fig. 3 demonstrating the differences clearly. The graphical representation of fitness values of both the algorithms are represented in Fig. 4.

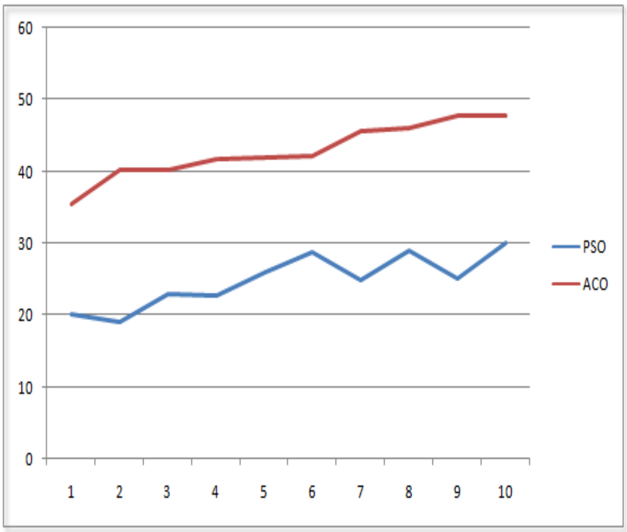

Fig. 4 Graphical representation of iterations (x axis) vs fitness values (y axis) of ACO and PSO

The fitness values are plotted against the number of iterations. The image enhancement problem is

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of maximization type and the graphs are plotted as shown in Fig. 4.

In this paper, the work on image enhancement has been done using the nature inspired algorithms where both are compared and contrasted different ways so as to make a comparative analysis, i.e, by using different operators, by using ACO and PSO nature inspired algorithms.

VI. CONCLUSION

In this research work, an experimental analysis of two metaheuristic nature inspired algorithms has been done namely ACO and PSO. To investigate the performance of both algorithms the problem of image enhancement is taken. It resulted in almost equal effectiveness but it has been observed from the results that there is a superior efficiency of ACO over the PSO. Comparatively PSO is simple in concept. These metaheuristic algorithms are statistical in nature and hence it is hard to conclude which algorithm performs better in a single run. Thus it is better to make several runs for better results. Both the algorithms are population based and use their respective information exchange mechanisms. The optimization of both the algorithms depends upon chosen parameters such as number of edge pixels, sum of pixel intensities etc.

VII. FUTURE SCOPE

Image enhancement provides a wide variety of approaches to modify the images to make them most appealing and enhanced. In the above work, it has been tried to enhance the image using image enhancement operators and selected NIA algorithms. In future, the research can be done using more parameters for the evaluation of fitness function and we can use a larger database for the possibility of better results. It may be a possibility to hybridize these algorithms in cloud computing or in other broader areas.

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