Retraction Notice

The Editor-in-Chief and the publisher have retracted this article, which was submitted as part of a guest-edited special section. An investigation uncovered evidence of systematic manipulation of the publication process, including compromised peer review. The Editor and publisher no longer have confidence in the results and conclusions of the article.

NS did not agree with the retraction. CC either did not respond or could not be reached.

Evaluation of bioinspired algorithms for image optimization

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Abstract. Steganography is a technique for concealing sensitive information behind a specific media source, such as an image, audio, or video file, in such a way that the concealed data are invisible to everyone. Many algorithms have been developed to optimize this process for better output. We aim to identify the different optimization algorithms used in image steganography after embedding the data to improve the resilience, visibility, and payload carrying capacity. Additionally, we highlight several bioinspired algorithms, including particle swarm optimization, ant colony optimization, firefly optimization, and artificial bee colony optimization, and evaluate through performance measures such as peak signal-to-noise ratio (PSNR) and mean square error (MSE). The performance metrics generated from the collected data indicate that the firefly method produced a higher PSNR and a lower MSE, namely 72.42 dB and 0.13, respectively. The methods are evaluated in terms of their ability for data embedding, robustness, and imperceptibility. © *2022 SPIE and IS&T* [DOI: 10.1117/1.JEI.31.4.041206]

Keywords: peak signal-to-noise ratio; mean square error; particle swarm optimization; ant colony optimization; firefly algorithm; artificial bee colony; image optimization; image steganography; bit error rate; bioinspired algorithms; computationally intelligent algorithms.

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1 Introduction

In today's rapidly expanding contemporary world, the communicator wants to communicate with confidence. Concealed communication enables sharing without revealing the identity of the communicator.[1] Concealed communication commences the new era in computer-internet technology, giving a new dimension to confidential information and engaging methods.[2] Concealed communication is nothing but hiding the personal information behind any other standard information by creating a hidden parallel communicating medium/channel between sender and receiver such that it goes completely unnoticeable. Such veiled channels prove to be advantageous over the encrypted channels as they maintain the unrecognizability of communication. Image files are the better mode of communication between the users, making it convenient to develop steganographic systems.[3] Steganography is defined as embedding the secret information that consists of two functions: stego function denoted by "F," and the inverse stego function denoted by the inverse of F^{-1}.[4] F takes the cover image and secret message as input and generates the stego image S. Alternatively, to recover the secret message, the F^{-1} is used. Mathematically, this is represented as $S = F(C, M)$ and $M = F^{-1}(S)$.[5] The first criterion is that the concealed data in the picture are imperceptible or undetectable while maintaining an acceptable visual quality. The second criterion is data embedding capacity: how much data can be inserted without impairing the image's quality. The third criterion to be considered is the robustness of acceptable distortion and its resistance to various attacks during transit. Once embedded in a picture, the data diminish the image, notifying the intruder to something odd. To avoid suspicion, the image is being optimized using various optimization algorithms. These algorithms help in maintaining all the three criteria mentioned above.

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There are various ways for secret information embedding in the cover image[6] such as spatial[7–11] and transform domain.[6,12] The former method is the simplest, since it embeds information in the smallest possible bit of each pixel of the cover picture. This is more vulnerable to frequency attacks. The latter method, on the other hand, transforms the cover picture to the frequency domain and embeds the secret information in the transform coefficients of the image.[13] Optimization is a process to figure out the best available inputs for attaining the maximum or minimum output with the least possible costing.[14] Optimizing any problem starts by selecting the design variable, then framing its limitations and objective function. An objective function assigns a value to selected variables according to the limitations and thus producing the optimum results. These problems are continuous and combinatorial problems that depend on the solutions available for the given problem. The former problems have countless solution through combinatorial problems provide fixed solutions. Swarm intelligence technique studies the behavior mutually within a decentralized and self-organized system.[15] The awareness of swarm intelligence is derived from the natural systems such as herds of animals, flocks of birds, and colonies of ants that can be pragmatically used to create an intelligent computational system. Swarm intelligence systems are made up of agents interacting holistically with each other and their environment. Such holistic interactions often result in the augmentation of global behavior.[16] In this paper, various swarm intelligence optimization techniques are reviewed incredibly naturally, along with their current research track. Section 2 discusses the critical conceptions of optimization techniques. Section 3 provides the view of current techniques of swarm intelligence optimization. Section 4 shows the comparison of these techniques, and the paper is hence concluded.

1.1 *Research Motivation*

Researchers have been paying close attention to bioinspired algorithms due to their potential to offer the best answer to current issues. These algorithms have proved their ability for providing the near optimal solution in various domains such as sentimental analysis, reinforcement learning, machine learning, and so on. The applicability of these algorithms on solving problems such as image optimization, complex optimization, and then using those images for security purposes using techniques such as cryptography, steganography (e.g., image) is a big challenge. The conventional optimization algorithms stuck around the local optima and are unable to provide the optimal or near optimal results.

1.2 *Research Contribution*

The main focus is to review the bioinspired algorithms for optimization problems available in the literature and to figure out the best algorithm that provides the optimal or near optimal solution. These algorithms are not complete in themselves, and many new optimization algorithms are being developed day-to-day. The process of development, implementation, and step-by-step description of algorithm is explained through the flow processes, and their applications on new areas of research have also been discussed.

2 Optimization Techniques

Optimization techniques figure out the optimal solution for the feasible solution of any given problem. Many such techniques solve functions with solo and multi variables with or without constraints. Various methods are used to derive these techniques such as linear method, nonlinear simulated annealing,[17] being inspired from metallurgical strengthening process, and genetic algorithms that find the best solution from a given population. Optimization techniques are classified as a traditional or heuristic-based approach. Traditional methods make use of differential calculus techniques[18,19] to find the optimal solution. The traditional approach is also known as direct or gradient methods.[20] It uses the values of the objective function; however, in gradient methods,[21] information from the derivative function is used. These methods provide efficient results in the uni-nodal simple objective function,[22] but they fail to provide efficiency in case of multi-nodal, complex problems. To get better results for complex problems, we make use of

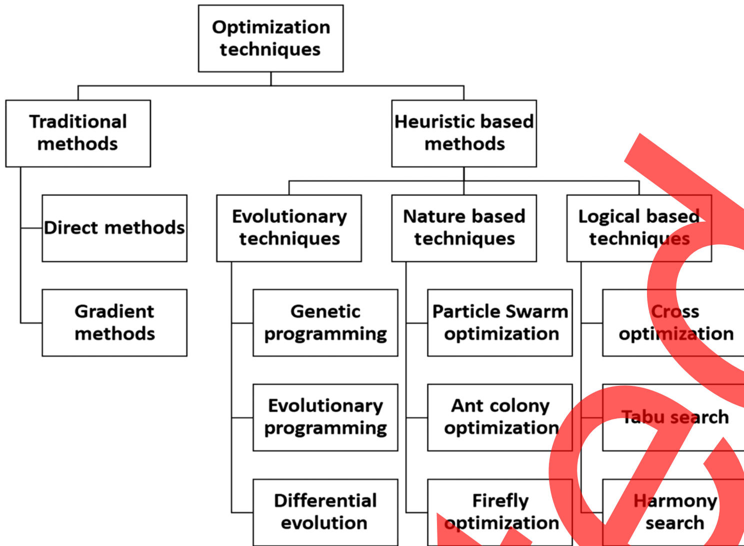

Fig. 1 Classification of bioinspired optimization techniques.

heuristic-based methods.[23] This technique can be classified as evolution-based,[24] nature-based swarm intelligence,[25] and logically based techniques,[26] as shown in Fig. 1.

Evolutionary techniques are inspired by Darwinian evolution.[27] These algorithms focus on the iterative generation of possible solutions to problems, that results in the selection of the best solution, which is determined by the output function. Some of the examples to show this include genetic[28] and evolutionary programming.[29] The naturally inspired algorithms are based on all agents' cooperative behavior communicating (directly or indirectly) to perform the intricate tasks. It is based on social insects' behavioral model such as ant, bees, termites, and so on. The logically based approach is established by combining mathematical techniques and logic programming. Mathematical techniques[30] are used to extract the structures and analytical techniques used to extort information to find the given problem's finest solutions. Examples for analytical-based optimization techniques include Tabu search, Cross optimization, and so on.

3 Nature-Based Bioinspired Optimization Techniques

Bioinspired techniques are the modern-day artificial intelligence method focusing on designing a multi-agent system applied in optimization, robotics, and so on. This method is based on the concept of collaboratively investigating a system composed of self-organizing components through decentralized control and self-organization processes inspired by social creatures. Numerous such algorithms are inspired by the behaviors of insects, including ant stigmergy, bird flocking, bee waggle behavior, and so on. Some of the swarm intelligence techniques are listed in Table 1.

Table 1 Different bioinspired algorithms.

Algorithm	Year	Author names	Inspiration
ACO[19]	1992	Dorigo	Behavior of ants foraging for food
PSO[16]	1995	Kennedy and Eberhart	Inspired by swarm
ABC optimization[31]	2005	Karaboga	Inspired by honeybees
FA[32]	2008	Yang	Inspired by fireflies' light emitting
Lion optimization algorithm[15]	2015	Yazdani and Jolai	A new population-based algorithm based on the lion's lifestyle and their cooperation characteristics

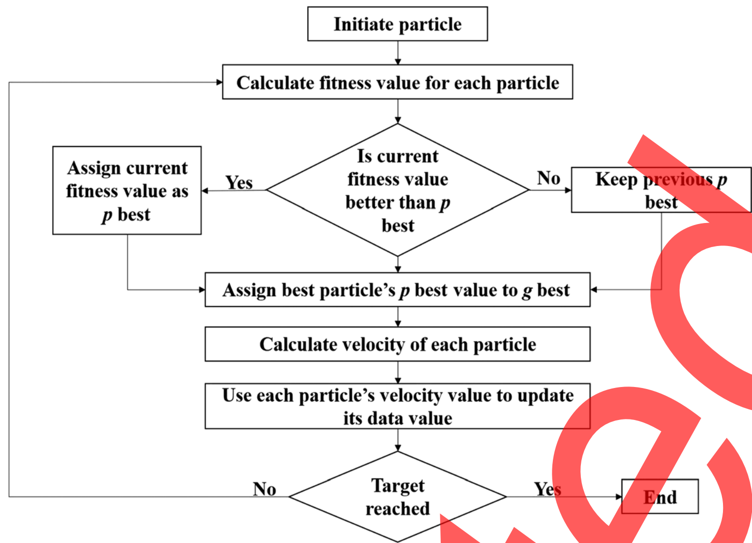

Fig. 2 Flow process of PSO algorithm.

3.1 *Particle Swarm Optimization*

Particle swarm optimization is a method that is population-based with a random probability distribution derived from social behaviors of animals and insects. This was originally proposed in 1995 by Kennedy and Eberhart. Individual swarm particles are described as feasible solutions using this approach. These particles traverse the problem-solving space in pursuit of the best solution. These particles then transmit their present locations to neighboring particles.[33,34] The procedure employed here is to accommodate the location of each individual wise particle according to (1) its speed and (2) the difference between the particle's current position, its neighbor's best position, and its yet to be determined best position. With the emphasis on the model, the swarm aligned itself for the search space producing high-quality solutions. The process flow for the particle swarm optimization (PSO) method is shown in Fig. 2.

3.1.1 *Research focus*

The research professionals have been using particle swarm intelligence technique to get a surge in payload carrying capacity to embed secret and important information, and find the optimum position to insert the secret and essential message. Table 2 shows the related literature for the PSO algorithm for embedding the secret data. In Ref. 33, PSO has been used for better quality steganographic image, using optimal substitution matrix to modify or convert the confidential messages/information. These updated messages are subsequently hidden in the discrete components (DC) to middle frequency components of the cover/main image's quantized discrete cosine transform (DCT) coefficients. Finally, the authors have used JPEG entropy coding to generate a secret info embedded image (JPEG) file. This method (proposed) has superior payload capacity and comparatively better image quality, thus providing better security. Bedi et al.[35] have used PSO method to provide the best pixel for embedding the secret information. Data veiling was done through least significant bit (LSB) method, where messages with multiple length were embedded in 1 to 4 least significant bits of image's pixels. The results obtained proved that the technique using PSO provides improved results against non-PSO methods. Yang et al.[9] have compared the PSO algorithm against traditional genetic algorithm for the problem of optimizing a stego image. In this work, the authors have proved that as it was easy to detect the secret message embedded through the LSB technique by steg analysis. So, they have embedded the secret message in the most significant bits using their proposed algorithm (PSO2011) and thus provided the better results. Khodaei and Faez[10] proposed the hybrid PSO algorithm. For an effectively data hiding, the authors have applied the PSO algorithm in combination with ant colony optimization (ACO) for the optimal pixels in original image for better image quality and

Table 2 Research focus: PSO-based optimization.

References	Year	Algorithm used	Benefits	Related parameters
36	2007	PSO and JPEG entropy coding	High payload capacity, better image quality, and high security	PSNR 38.02, capacity 73,728 bits, file size 27 kb, and computational time 35.7 s
35	2011	4-bit LSB and PSO	Less divergence and greater similarity	PSNR 52.45, MSE 0.36, and SSIM 0.99
37	2017	PSO2011	Optimized stego image and better results	Popsize 20 and generations 4
38	2014	Hybrid PSO (PSO combined with ACO)	Better image quality and high security	PSNR 38.41
39	2013	LSBMR using PSO	Better image quality and high security	PSNR 60.55 and MSE 0.00072
40	2016	PSO combined with GA	High security and efficient encryption	PSNR 78.29 and MSE 0.3

improved security. Bajaj et al. [11] proposed a method LSB matching revisited (LSBMR) using PSO where PSO algorithm in line with the size of secret information, selected the regions where the information can be stored. Further in the next step, the threshold values of selected region of image are optimized. The results show that high embedding capacity along with better image quality was achieved using proposed method. To provide secure and better encryption of images, Barni et al.[12] have combined PSO with a genetic algorithm. The proposed methodology improves the encryption ratio as well as providing less mean square error (MSE) for encryption and decryption and high values of peak signal-to-noise ratio (PSNR).

3.1.2 *Algorithm description*

The method searches for particles in a swarm that is modified after each iteration. To find the optimum solution, each particle travels in the direction of its previous best position, denoted by the term pbest position, and the global best position, denoted by the term gbest position in the swarm[41]

$$p\text{best}(i,t) = \arg_{k=1,\dots,t} \min[f(P_i(k))], \quad i\epsilon\{1,2,\dots,N_p\}, \tag{1}$$

$$g\text{best}(t) = \arg_{k=1,\dots,N_P} \min[f(P_i(k))], \quad \text{where } k = 1,\dots,t. \tag{2}$$

Here, i denotes the particle index, N_P denotes the total number of particles, t denotes the current iteration, f denotes the fitness function, and p denotes the particle's location. The following equations update the velocity V and location P of particles[42]:

$$V_i(t+1) = \omega\, V_i(t) + c_1 r_1 (p\text{best}(i,t) - P_i(t)) + c_2 r_2 (g\text{best}(t) - P_i(t)), \tag{3}$$

$$P_i(t+1) = P_i(t) + V_i(t+1), \tag{4}$$

where ω represents the inertia weight that is used to balance global and local exploration, r_1 and r_2 are uniformly distributed random variables in the range [0, 1], and c_1 and c_2 are positive constant parameters, also called acceleration coefficients. The first term in Eq. (3) is termed inertia. It supplies the required momentum for particles to wander throughout the search space. The second component, dubbed the cognitive part, urges particles to gravitate toward their optimal positions. The third component of Eq. (4) is the combined impact of all particles on finding the global optimum solution, often referred to as the collaboration component.

3.2 *ACO*

ACO was initially introduced by Dorigo.[43] Their vision behind this technique comes from real ant's behavior, which they used to solve various types of optimization problems. The authors observed that ants could find the shortest path to their food source without communicating directly with it. Initially ants follow a random path from their nest toward their food. During their movement, they release one special body chemical, a pheromone, all along their trail. Naturally, the ants that have chosen the shortest path will have more traces of pheromone as compared with the longest path, as the smell of the chemical attracts more ants and the chemical on longer paths dries up after some time, thus making the followers clueless at some span of time along the path. So, more ants end up following the shortest path from food to nest. The longest path also becomes less usable or followed the path as after some time the pheromone gets evaporated. Due to this entire process, there is more pheromone along the shortest path thus attracting attracts remaining ants. So, Dorigo and Stützle derived an artificial ACO method by studying this entire behavior mechanism.[44–48] The ACO technique is based on probabilities calculations for finding the best path through graphs. In this method, a solution for a given problem is shown by the ant's most followed path. The amount of increase in pheromone corresponds directly to the quality of candidate solution. Proportionately more ants will choose the path with more pheromone. Thus, the shortest path having more pheromone becomes the best path.

3.2.1 *Research focus*

The researchers have been using ACO technique to improve payload capacity to embed the secret and important information and find the optimum position to embed the secret bits. Khan[49] has used ACO to detect the complex region of the original image and then used LSB to hide the secret message in the detected complex's region pixel. The least significant bits of complex region pixels are identified and then substituted by bits containing messages. The ACO-based data hiding is both efficient and secure, which results in better steganographic image quality, with significantly higher PSNR, and an acceptable data hiding capacity. Zghaer and Hashem[50] have proposed an ACO-based image steganography to improve the spatial image steganography to hide the data randomly in the main/cover image and using that time and again. ACO algorithm finds best path through the pixels within the block. To reuse the same cover, the proposed technique divides the messages in bits within the block and hides those bits in second optimal pixel. The results show that the ACO algorithms are more suitable and effective for steganography. Hsu and Tu[51] have addressed the two main issues after embedding the message in the original image, i.e., robustness and stego image quality. The authors here have used the ACO algorithm for developing the best matrix for LSB substitution. The results prove that ACO can find the best matrix for LSB substitution much more efficiently and can also improve/maintain the quality of stego images. Navdeepkaur[38] proposed the hybrid ACO algorithm. The author has applied the ACO algorithm by hybridizing it with PSO for data concealment thereafter to find an optimal pixel in the original image and better image quality and high security. The related literature for ACO technique for embedding the data is presented in Table 3.

Table 3 Research focus: ACO-based optimization.

References	Year	Algorithm used	Benefits	Related parameters
49	2018	ACO	High payload capacity and better image quality	PSNR >50 and capacity 0.36 bpp
50	2017	ACO	More efficient, good security, and better image quality	PSNR 80.08 and MSE 0.00063
51	2010	LSB substitution based on ACO	High security and better image quality	PSNR 34.58
38	2014	ACO combined with PSO	Better image quality and high security	PSNR 38.41

3.2.2 *Algorithm description*

A digital image of size $M \times N$ is considered as a cover medium in the initialization stage. In the next step, i.e., the construction phase, one ant is randomly selected out of total K ants. The ant travels from initial pixel (x, y) to its adjacent pixel (i, j), with a transition probability $p(x, y), (i, j)$, which is defined as follows[52]:

$$p^{(n)}_{(x,y),(i,j)} = \frac{(\tau^{(n-1)}_{i,j})^{\alpha}(\eta_{i,j})^{\beta}}{\sum_{(i,j)\varepsilon\Omega_{(x,y)}}(\tau^{(n-1)}_{i,j})^{\alpha}(\eta_{i,j})^{\beta}}, \tag{5}$$

where $\tau^{(n-1)}_{i,j}$ gives the value of pheromone at pixel (i, j), $\Omega_{(x,y)}$ is the neighbor pixel of (x, y), $\eta_{i,j}$ represents the heuristic information at pixel (i, j),α and β represent the influence of pheromone and heuristic matrix, respectively.

The heuristic information is calculated as

$$\eta_{i,j} = \frac{V_c(C_{i,j})}{Z}, \tag{6}$$

where Z is the normalization factor, which is stated as follows:

$$Z = \sum_{i=1:M}\sum_{j=1:N} V_c(C_{i,j}), \tag{7}$$

where $C_{i,j}$ is the intensity level pixel of image c, and $V_c(C_{i,j})$ is calculated as follows:

$$V_c(C_{i,j}) = f\begin{pmatrix} |C_{i-2,j-1} - C_{i+2,j-1}| + |C_{i-2,j+1} - C_{i+2,j-1}| \\ +|C_{i-1,j-2} - C_{i+1,j+2}| + |C_{i-1,j-1} - C_{i+1,j+1}| \\ +|C_{i-1,j+2} - C_{i-1,j-2}| + |C_{i,j-1} - C_{i,j+1}| \end{pmatrix}. \tag{8}$$

The third stage is the called updating stage, where a two-step method is used for updating pheromone matrix. The first update precedes the movement of each ant, which is expressed as[53]

$$\begin{cases} (1-\rho), & \tau^{(n-1)}_{i,j} + \rho, \Delta^{(k)}_{i,j} \\ \tau^{(n-1)}_{i,j} & \text{otherwise} \end{cases} \quad \text{if}\, i, j \,\text{is visited by ant}\, K, \tag{9}$$

where ρ is the evaporation rate and $\Delta^{(k)}_{i,j}$ is determined by heuristic matrix and equals $\eta_{i,j}$. Once the movement of all ants is complete, the second update task is performed, which is expressed as[54]

$$\tau^{n} = (1-\varphi).\tau^{(n-1)} + \varphi.\tau^{(0)}, \tag{10}$$

where ψ represents the decay coefficient pheromone. In the final stage, the decision process is executed using the value of the position of pheromone. Thereafter, the obtained value is compared with threshold value. If the obtained pheromone's value is greater than threshold, then it is marked as part of the complex region pixel; otherwise, it is marked as smooth region.

3.3 *Firefly Algorithm*

Firefly algorithm (FA) was introduced by Yang in 2008. It is based on methodology that randomizes the value as it searches for a complete set of solutions. Thus, we can say that it is an algorithm having random probabilistic distribution. In this method, Yang studied the behavior of real fireflies and analyzed the same for coming up with a solution that reflects

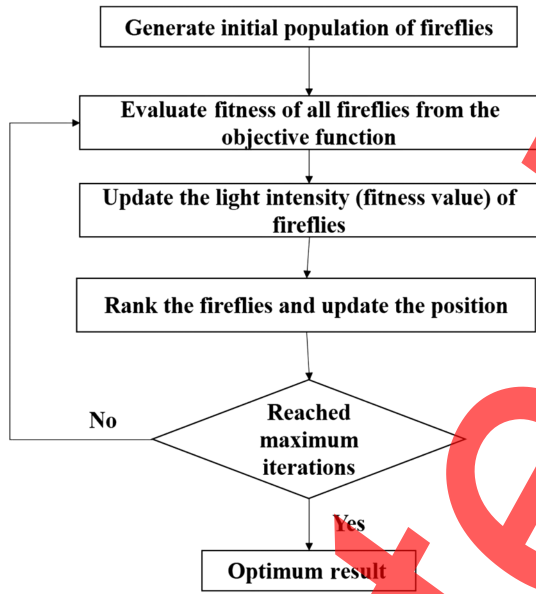

Fig. 3 Flow process of FA.

the same behaviors. The fireflies are flying insects,[32] whose bodies emit light differently. Each firefly's light intensity as well as luminosity is different. With the help of these light-emitting patterns, they communicate with each other, sending some important situational messages and also attracting the opposite sex for mating. By taking inspiration from these insects, Yang[55] developed a method that is also known as FA technique. The principle method of fireflies depends on the attractiveness of fireflies, their inter-relation between distance and luminosity. The landscape of objective function is used for calculating the brightness of the light emitted. The main advantage point of FA is that it divides the available population/group automatically, whereupon it finds the best solutions when the subdivision group's size increases than the total modes. Normally FA is used for solving multidimensional problems of optimization. The process flow for the FA is shown in Fig. 3.

3.3.1 *Research focus*

Research professionals have been using FA optimization technique to boost the data holding capacity to embed the secret and important information and find the optimum position to insert the secret and important message. Amsaveni and Kumar[56] have used FA to find the optimal location to hide the secret message using reversible data hiding technique so as to ensure high data security. The authors have used the histogram shifting technique for implanting secret information in the main/cover image. Tariq et al.[57] have used FA to figure out best position in the original image to LSB embed the secret message. The results generated proved that the FA is efficient in term of better image quality and security. The related literature for the FA for data veiling in cover images and finding the best location is presented in Table 4.

Table 4 Research focus: firefly-based optimization.

References	Year	Algorithm used	Benefits	Related parameters
56	2015	FA	Better image quality and high security	PSNR 52.86 and MSE 0.0007
57	2017	Firefly with LSB	More efficient, good security, and better image quality	PSNR 69.44 and MSE 0.00063

3.3.2 *Algorithm description*

This algorithm works on three rules:

Rule 1: It asserts that all fireflies are gender neutral and that any firefly may be attracted to another firefly.
Rule 2: The allure among the fireflies is proportional to the brightness, which is further proportional to their distance. Thus, for any two emitting fireflies, the less bright firefly moves toward brighter one. In case where there is no brighter one, then that firefly moves randomly.
Rule 3: The brightness of a firefly is related to the landscape of the goal. The brightness changes according to the objective function's value, i.e., for maximum value corresponds to maximum brightness and therefore peak objective value.

This implies a minimization problem; the light intensity is inversely proportional to distance as expressed as follows:

$$I \ \alpha \ \frac{1}{r^2}, \tag{11}$$

where r is the distance and I is the intensity. With regard to distance, brightness follows a similar law to that of light intensity. Additionally, consider light travelling through a material having a coefficient of light absorption. A firefly's brightness at a distance r is given as[58]

$$\beta = \beta_0 e^{-\gamma r^2}, \tag{12}$$

where β and β_0 are the brightness of a firefly at r and at $r = 0$, respectively. Using the following equation, a solution x_i will be attracted by a brighter firefly designated as x_i[59]

$$x_i = x_i + \beta_0 e^{-\gamma r^2}(x_j - x_i). \tag{13}$$

The random movement of firefly is given as

$$x_i = x_i + \alpha(\mathrm{rand}() - 0.5). \tag{14}$$

Combining Eqs. (13) and (14) results as follows:

$$x_i = x_i + \beta_0 e^{-\gamma r^2}(x_j - x_i) + x_i = x_i + \alpha(\mathrm{rand}() - 0.5\ ). \tag{15}$$

The above Eq. (15) is for brighter firefly x_j. If incase there is no brighter firefly than, there is a random move as shown in Eq. (14).

3.4 *Artificial Bee Colony Optimization Algorithm*

The artificial bee colony (ABC)[31] is a higher-level solution heuristic systematic method that is derived from bees' behavior to find a good optimizing solution. ABC[60] has been detailed out of analyzing the behavior of honeybees in their quest for finding food sources. The key indicators and performance pattern is analyzed once the final process of this method, i.e., solution seeking process, is executed. These key components, which are analyzed after the solution process, are: The source of food of bees, value of fitness, and bee agents.[61] The source of food discussed above illustrates the feasible optimizing solution. Value of fitness is associated with the objective function. Bees in bees' agents segment discussed in ABC can be characterized as employees (bees), onlookers, and scouts. Figure 4 shows the process flow for ABC method.

3.4.1 *Research focus*

The researchers have been using ABC algorithms for various optimization problems. The literature of related research articles for ABC algorithm is shown in Table 5. Banharnsakun[62] has used ABC algorithm with LSB-based image steganography and compared it with the other existing techniques and found ABC algorithm better. The PSNR value obtained for the algorithm

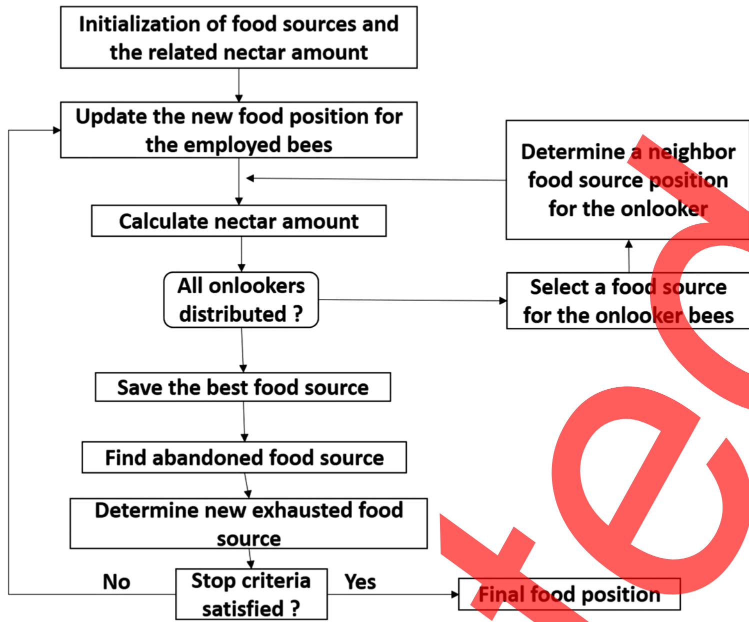

Fig. 4 Flow process of for ABC optimization algorithm.

Table 5 Research focus: ABC-based optimization.

References	Year	Algorithm used	Benefits	Related parameters
62	2017	ABC algorithm with LSB	Better image quality and high security	PSNR 56.39 and BER 7.42%
63	2017	data encryption standard, discrete wavelet transform with ABC, and scrambling algorithm	High embedding capacity, better image quality, and high security	PSNR 48.13 and MSE 0.011

is 56.39, which is the highest among all other existing techniques. The other parameter taken into consideration is average bit error rate (BER), which is found to be 7.42% which is the lower among all other existing techniques. The algorithm offers good performance in terms of quality and security but could not offer high embedding capacity. Muthyala et al.[63] have used DES algorithm for encryption of the secret message along with discrete wavelet transforms to keep the original image intact. ABC algorithm is used to boost the data veiling capacity, and the scrambling algorithm helps in enhancing proposed algorithm's security. The results obtained after the experimentation shows that PSNR values increase by 10.13% and MSE decreases by 64.3%.

3.4.2 *Algorithm description*

An artificial bee selects a food source based on its probability value, pi, which is represented as[31]

$$pi = \text{fiti} \sum \text{fitnSNn} = 1, \tag{16}$$

where fiti is the fitness value of solution I, which equals the nectar content of the food source in position I, and SN is the number of food sources, which equals the number of employed bees or observer bees. ABC generates a candidate food position from an existing one in memory using the following[64]:

$$V_{ij} = X_{ij} + \varnothing_{ij}(X_{ij} - X_{kj}), \tag{17}$$

where $k \in 1, 2, \ldots, \text{SN}$ and $j \in 1, 2 \ldots D$ are selected at random. Although k is chosen at random, it must be distinct from i. ij is a random value in the range [−1,1]. It regulates the generation of neighboring food sources and visually compares two food locations using a bee. As the disparity between decreases, the position's disturbance decreases as well. The step time is adaptively lowered as the search proceeds toward the best solution in the search space. When a parameter's value exceeds a preset threshold, it is reset to an acceptable value. The scouts replace the food source from which the bees have abandoned nectar with a new food source. This is performed by randomly creating a new position and substituting it for the one that was abandoned. After a given number of cycles, if a position cannot be improved further, it is assumed that the food source has been abandoned. The number of specified cycles is referred to as the abandonment threshold. Consider the X_i source that has been abandoned and the j\$1, 2, …, $j1, 2, \ldots, D$. The scout then locates a replacement food source for X_i, denoted as[65]

$$X_i^j = X_{\min}^j + \mathrm{rand}[0,1](X_{\max}^j - X_{\min}^j). \tag{18}$$

As seen in the preceding methodology, ABC is based on the probability of locating food and providing the shortest journey from the source to the destination. Additionally, we can improve the speed/pace of solution discovery by integrating other intelligent swarm optimizations such as fitness dependent optimizer, which is primarily concerned with this aspect of the algorithm.[66]

A number of academics use the algorithms outlined above in a variety of contexts and circumstances. The selection scheme and the searching algorithm can be balanced by combining these algorithms to form a full global algorithm and other algorithms.[67,68]

4 Research Methodology

Several research and review papers on optimization techniques for image steganography were reviewed. Then the above explained algorithms were finalized and implemented based on the literature. The implementation is done in MATLAB. The motive behind the implementation of algorithms was to analyze the robustness, imperceptibility, and payload capacity of the algorithm. The results thus obtained were evaluated on certain parameters such as peak signal to ratio, MSE, BER, and structural similarity index (SSIM). The review analysis was done on two main parameters PSNR and MSE for the existing literature. These parameters were then reviewed on four main algorithms, such as PSO, ACO , FA, and ABC, and their properties, behaviors, and features were analyzed. The performance values of these are analyzed and graphically presented. The comparative analysis of the values has also been done. Following this, a detailed review analysis on the existing results and results obtained with different parameters are analyzed; conclusion and future scope are derived and discussed.

5 Performance Metrics

The algorithms' performance is quantified using the following different parameters.

5.1 *PSNR*

PSNR is mathematically denoted by Eq. (19). The higher the ratio is, the higher the picture quality is

$$\mathrm{PSNR} = 10 \log_{10} \frac{255^2}{\mathrm{MSE}}. \tag{19}$$

5.2 *MSE*

MSE is the inverse of PSNR. It is mathematically represented as Eq. (20). Reduce the settings to improve the picture quality

$$\mathrm{MSE} = \frac{1}{m \times n} \sum_{i=1}^{m} \sum_{j=1}^{n} \| O(i,j) - s(i,j) \|^2. \tag{20}$$

5.3 *SSIM*

The SSIM algorithm determines the similarity of two pictures. Equation (21) defines it as follows:

$$\mathrm{SSIM} = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}, \tag{21}$$

where μ_x,σ_x^2, μ_y, and σ_y^2 denote the average and variance of x and y, respectively, σ_{xy} denotes the covariance of x and y, c_1 and c_2 represent constants with values $c_1 = m_1 L_2$ and $c_2 = m_2 L_2$, respectively, with m_1 and m_2 having values 0.001 and 0.003, respectively, and L being the pixel range.

5.4 *BER*

BER is the rate at which errors occur during digital data transmission. It is stated in the following way in Eq. (22):

$$\mathrm{BER} = \frac{N_{\mathrm{Err}}}{N_{\mathrm{bits}}}, \tag{22}$$

where N_{Err} denotes the number of bits received with an error and N_{bits} denotes the total number of bits.

6 Comparative Analysis

The bioinspired algorithms have been thoroughly researched, and a comparison of the various algorithms has been made based on specific metrics such as PSNR, MSE, BER, and SSIM. The comparison is-also performed on the basis of the characteristics of the respective algorithms, as shown in Fig. 5. This comparison of the algorithms is also performed through the experimental results obtained after their implementation in MATLAB. As shown in Table 6, PSNR value is higher in case of FA and is lowest in case of ABC algorithm, i.e., 72.42 and 50.61, respectively. The values of MSE is obtained minimum for firefly, i.e., 0.031, and maximum in case of ABC algorithm. The BER for firefly is minimum, i.e., 0.10, and SSIM is 0.96.

Parameters involved	PSO	ACO	FA	ABC
Inspiration	Activities of the group of birds & fishes	Activities of real ant colonies	The light emitting pattern of fireflies	Activities of group of honey bees
Navigation strategies	Follow the bird which is nearest to the target	Move randomly and release pheromone alongside	Moves randomly, firefly attract toward the brighter firefly	Moves in three phases: employed bees, onlooker bees, and scout bees
Selection of final Path	1. It depends on the value of p best variable. Bird possessing 2. The highest value is followed	Amount of pheromone on the route. The highest amount is accepted	It depends on the intensity of flashing light. Highest intensity is chosen	1. This is done by onlooker bees based on the information shared by employed bees 2. Waggle dance
Returning to nest	Particles traverse while following the one	Ants senses pheromone on the route on the way back returning.	Uses the flashing lights of fireflies while returning	Scout bees abandon and then look for other food source
Advantages	1. Intelligence based, applicable to scientific research and engineering use 2. No overlying and transmutation calculation 3. Very simple algorithm. Possess large optimization ability as compared with other algorithms 4. Adoption of real number code and decided directly by the solution	1. Powerful robustness. 2. Works on distributed computation thus avoiding premature convergence. 3. Very adaptive nature for any changes. 4. Positive feedback oriented assisting in the discovery of good solutions. 5. Very useful in dynamic applications	1. Naturally effective with highly, non-linear, multi-modal optimization problems. 2. Doesn't consider velocities of fireflies and hence no problems are associated with velocity 3. High speed convergence. 4. Very flexible for integration with other optimization techniques	1. Simplicity, flexibility, and robustness 2. Ability to explore local solutions 3. Ability to handle objective cost 4. Application to complex functions
Disadvantages	1. Weak local search ability. 2. Cannot support the problems of scattering, non-coordinate systems. 3. The tendency to a fast and premature assembly in mid optimum points	1. Uncertain time convergence. 2. Difficult coding 3. Slight weaker in performing for the local optimal solution. 4. Insufficient in case of exploration	1. Static parameters 2. Fails to retain the history of the better situation of each firefly thus moving regardless of the previous better situation, thus sometimes missing the situation 3. Often trapped & unable to get rid of local search	1. Lack of use of secondary information 2. Slow in sequential processing 3. High number of objective function evaluation 4. Requires new fitness test on new algorithm parameters
Applications	. Neural networks · Telecommunications · Control · Data mining · Design · Combinatorial optimization · Power systems · Signal processing etc,	· Scheduling problems · Assignment problems · Vehicle routing · TSP · SPAM detection · Image processing etc,	. Digital image compression and image processing · Feature selection and fault detection · Antenna design · Structural design · Scheduling · Clustering · Dynamic problems etc,	. Remote sensing · Feature selection and optimization · Signal processing · Video processing · Digital image processing · Numerical problems etc,

Fig. 5 Comparison of bioinspired algorithms based on their characteristics.

Table 6 Comparison based on PSNR for existing swarm intelligence algorithms.

Algorithm	PSNR	MSE	BER	SSIM
PSO	54.25	0.52	0.90	0.63
ACO	66.34	0.51	0.17	0.92
Firefly	72.42	0.031	0.10	0.96
ABC	50.61	1.21	1.01	0.75

The algorithms are also compared using the existing literature through PSNR and MSE values. As shown in Table 7, Kumar and Paliwal[40] achieve the higher PSNR values, whereas Raja and Baburaj[39] receive minimum MSE values. The PSO algorithm is also evaluated on PSNR. Kumar and Paliwal[40] representing-the highest value, whereas Li and Wang[36] representing the lowest value (see Table 7).

Now, the-performance-of ACO algorithm is-evaluated on PSNR and MSE values with the current state-of-the-art (see Table 8). Zghaer and Hashem[50] representing the highest value, whereas Hsu and Tu[51] representing the lowest value.

The performance of FA is evaluated on PSNR and MSE values with the techniques presented in existing literature (see Table 9). Zghaer and Hashem[50] representing the highest value, whereas Hsu and Tu[51] representing the lowest value. Tariq et al.[57] representing the highest value of PSNR, whereas Amsaveni and Kumar[56] representing the lowest value. Tariq et al.[57] representing the lowest MSE value, whereas Amsaveni and Kumar[56] representing the highest value. The implemented FA achieves the 72.42 dB PSNR value and 0.031 MSE value, which is better.

Performance-of the-ABC algorithm is evaluated using PSNR and MSE values (see Table 10). Banharnsakun[62] representing the highest value, whereas Amsaveni and Kumar[56] representing the lowest value. The images were taken from signal and image processing institute dataset.[69]

Table 7 Comparison on PSNR and MSE for PSO algorithm.

References	Year	PSNR	MSE
36	2007	38.02	—
35	2011	52.45	0.36
39	2013	60.55	0.0007
40	2016	78.29	0.3
PSO (basic)	—	54.25	0.52

Table 8 Comparison on PSNR and MSE for ACO algorithm.

References	Year	PSNR	MSE
49	2018	50	—
50	2017	80.08	0.00063
51	2010	34.58	—
32	2013	38.41	—
ACO	—	66.34	0.51

Table 9 Comparison on PSNR and MSE for FA.

References	Year	PSNR	MSE
5	2015	52.86	0.0007
57	2017	69.44	0.00063
FA	—	72.42	0.031

Table 10 Comparison on PSNR and MSE for ABC algorithm.

References	Year	PSNR	MSE
62	2017	56.39	—
63	2017	48.13	0.011
ABC	—	50.61	1.21

7 Conclusion

The above analysis concludes that different algorithms give optimum results for different parameter values. For instance, the FA performs better in achieving the highest PSNR values and the lowest MSE values. Similarly, the ACO algorithm's performance comes after therein, followed by PSO algorithm and ABC optimization-algorithm, respectively. The existing literature researchers have combined these optimization techniques with other algorithms to achieve the optimum results. This paper focuses on selecting the optimization algorithm for embedding the secret bits into the image and the same is done using discrete wavelet transforms. However, in future, the techniques, such as least significant bit, most-significant bit, and so on, will also be implemented. Second, the optimization algorithms implemented above are tested with limited payload capacity; however, these would be tested with higher payload capacity and factors such as imperceptibility and robustness will also be considered in future. One of the limitations of this research is that it is assumed that the secret key is preshared between the sender and receiver; however, in future, the research would focus on sharing the secret key between the two parties.

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