



UTM
UNIVERSITI TEKNOLOGI MALAYSIA

**INTERNATIONAL JOURNAL OF
INNOVATIVE COMPUTING**

ISSN 2180-4370

Journal Homepage : <https://ijic.utm.my/>

Image Fusion Algorithm using Grey Wolf optimization with Shuffled Frog Leaping Algorithm

Afrah U Mosa¹

Informatics Institute for Postgraduate Studies
Iraqi Commission for Computers and Informatics
Baghdad, Iraq
Email: phd202110688@iips.icci.edu.iq

Waleed A Mahmoud Al-Jawher²

Department of Electronics and Communication Engineering
Uruk University
Baghdad, Iraq

Submitted: 30/11/2022. Revised edition: 31/3/2023. Accepted: 31/3/2023. Published online: 13/9/2023

DOI: <https://doi.org/10.11113/ijic.v13n1-2.412>

Abstract—Data fusion is a “formal framework in which are expressed the means and tools for the alliance of data originating from different sources”. It aims at obtaining information of greater quality; the exact definition of 'greater quality will depend upon the application. It is a famous technique in digital image processing and is very important in medical image representation for clinical diagnosis. Previously many researchers used many meta-heuristic optimization techniques in image fusion, but the problem of local optimization restricted their searching flow to find optimum search results. In this paper, the Grey Wolf Optimization (GWO) algorithm with the help of the Shuffled Frog Leaping Algorithm (SFLA) has been proposed. That helps to find the object and allows doctors to take some action. The optimization algorithm is examined with a demonstrated example in order to simplify its steps. The result of the proposed algorithm is compared with other optimization algorithms. The proposed method's performance was always the best among them.

Keywords—Etaheuristic optimization, grey wolf optimization, Shuffled Frog Leaping Algorithm, prey, Image fusion

I. INTRODUCTION

Nowadays, image processing is used in various fields such as the medical field, aerospace, road traffic, image reconstruction, and others. Image processing has many important techniques and one of these techniques is image fusion. Image fusion means extracting important information from multiple images and merging them into one. This technology is used in many fields, and one of the most important uses in clinical diagnosis is the medical field. When using any technology in the medical field, accuracy must be a major criterion because it is related to the patient's life. In order to achieve the best accuracy, many researchers have sought to employ metaheuristic research methods to obtain the best

results for image fusion. The key to getting a good result from the fusion process is that the images used in the process contain valuable information. The proposed algorithm employs grey wolf optimization algorithm with Shuffled frog leaping algorithm to try to find suspicious objects in the human body with finding the best positions for the camera to take pictures of.

Many researchers have tried to use optimization algorithms to improve the images generated by the Fusion process. Azarang and Ghassemian (2017) suggested a new image fusion algorithm for use in remote sensing applications. The band coefficients of multispectral images are calculated using the least squares approach to find the primitive detail map. They used particle swarm optimization (PSO) to determine the suitable weights to combine panchromatic (Pan) and multispectral [1]. Shehnaz *et al.* (2021) also used the PSO algorithm in the medical image fusion process. They used discrete wavelet transform (DWT) to decompose the input images then PSO is used to compute the optimum weight to the energy bands to be integrated by the fusion process [2], [3], [4], [5].

Many other researchers have suggested different ways to improve the Fusion process using optimization algorithms, some of them have combined more than one algorithm to get better results such as Dutta and Banerjee (2020) [3]. Several authors used Wavelet and Multiwavelet transform [6], [7], [8], [9], [10] and their generation in the different steps of the fusion process, namely Daniel (2018) [11], [12].

In this paper, we propose a new method to identify the best images entering the fusion process. Our algorithm merges GWO and SFLA.

In the next sections, we will explain the basic principles that we relied on and then explain the proposed algorithm in detail.

II. GREY WOLF OPTIMIZATION (GWO)

This algorithm was inspired by the life and social behaviour of grey wolves to direct the optimization process. Gray wolves are predators that live in a pack. The size of the pack is usually between 5-12 wolves, distributed within a certain social hierarchy as shown in Fig. 1.

At the top of this pyramid is the leader of the pack which is called alpha wolf (α). The alpha wolf can be male or female, whose responsibility is to make decisions about the pack, such as hunting decisions, sleeping place and moving. All members of the pack should follow the orders of the alpha wolf and it is not necessary that it be the strongest among them, but it is the best in management.

The alpha wolf is followed by a number of subordinate wolves in the hierarchy called beta wolves (β). These beta wolves help the alpha in making decisions and other activities. Beta wolves follow the orders of the alpha wolf but they are commanding wolves on the other levels.

The next level in the pyramid are delta wolves (δ), which are responsible for tasks such as hunting, scouting, and caring for weaker individuals. At the lower level of the pyramid are the Omega wolves (ω) and those who follow the orders of wolves from all other levels.

In the GWO algorithm, the social hierarchy as well as the hunting technique of these wolves are simulated and modelled mathematically. In the next section we will discuss the hunting technique and the mathematical models [12], [13].

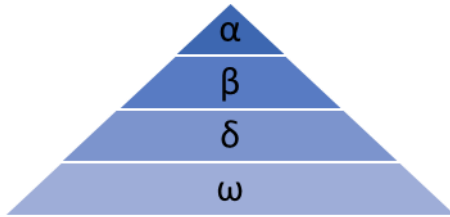


Fig. 1. Hierarchy of grey wolf (dominance decrease from top down)

A. Hunting technique and mathematical models

The grey wolves hunting technique includes three stages. It begins with finding prey and encircling it, then hunting it, and finally attacking it.

The following is a representation of these three stages and the mathematical models for each one.

B. Encircling prey

Grey wolves can locate the position of prey and encircle it. This is the first step in hunting process. GWO algorithm proposed following equations to represent this stage mathematically.

$$\vec{D} = |\vec{C} \cdot \vec{X}_p(t) - \vec{X}(t)| \quad (1)$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \quad (2)$$

Where t is the current iteration. X_p is the position of the prey while X is the position of a grey wolf. A and C are the coefficients vectors which are calculated as following

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \quad (3)$$

$$\vec{C} = 2 \cdot \vec{r}_2 \quad (4)$$

\vec{a} values decreased from 2 to 0 over the iterations. \vec{r}_1 and \vec{r}_2 are random in range (0,1).

The position of wolves changing by adjusting A and C values to reach the best position with respect to prey position. The random vectors r_1 and r_2 enable the wolves to move to any position around the prey.

C. Hunting

The alpha wolf guides the hunt. Sometimes, beta and delta wolves participate also. GWO algorithm considers the best solution as alpha and the next two best are considered as beta and delta. The algorithm saves these three solutions and updates the positions of the other agents according to them. This hunting process is modeled as the following.

$$\vec{D}_\alpha = |\vec{C}_1 \cdot \vec{X}_\alpha(t) - \vec{X}(t)| \quad (5)$$

$$\vec{D}_\beta = |\vec{C}_2 \cdot \vec{X}_\beta(t) - \vec{X}(t)| \quad (6)$$

$$\vec{D}_\delta = |\vec{C}_3 \cdot \vec{X}_\delta(t) - \vec{X}(t)| \quad (7)$$

These three equation to calculate the distance between the search agent (a wolf) and the three best solutions (α , β , δ). Then three new positions for the agent are calculated depending on the three calculated distances ($\vec{D}_\alpha, \vec{D}_\beta, \vec{D}_\delta$) by using the following equations.

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha \quad (8)$$

$$\vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta \quad (9)$$

$$\vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta \quad (10)$$

The proposed new position will be the arithmetic mean of these three positions equation (11).

$$\vec{X}_{t+1} = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (11)$$

D. Attacking

At the end of hunting process the grey wolves attack the prey after approaching it. To represent that mathematically, the value of a is decrease and that will reflect to the value of A . When the value of A is in range $[-1, 1]$, the next position of the

wolf can be at any point between its position and the prey's, so the position is suitable for attacking.

III. SHUFFLED FROG-LEAPING ALGORITHM

The Shuffled Frog-Leaping Algorithm (SFLA) is meta-heuristic search algorithm which inspired by nature. Imagine a group of frogs leaping in a swamp to get the stone that has the most food accessible among the many stones that are scattered across the swamp. The frogs are able to contact with one another in order to learn from one another and use that knowledge to enhance their memes. When a meme is improved, each individual frog's position is adjusted to be optimal by altering the step size of the leaps.

SFLA attempts to avoid falling into the local maximum problem by performing a local search and exchanging global information. It combines two optimization algorithms together which are Shuffled complex evolution algorithm (SCE) and Particle swarm optimization (PSO). In the next sections, we will discuss the basic principles of both algorithms [14], [15], [16], [17], [18], [19].

A. Shuffled Complex Evolution Algorithm (SCE)

SCE algorithm philosophy is that, treating the global search as a process of natural evolution. This algorithm partitions the population into several complexes. Each one of complexes evolves independently then they are forced to mix and shuffle together to form new complexes. That helps to share information of each complex globally.

It is necessary to select the best parents to contribute to generate the next offspring in order to ensure that the evolution process is competitive [17]. To prevent the process of evolution from getting stuck in poor or unpromising place in the solution space, there are also random introductions of offspring within the valid space.

The worst element in the present sub complex is replaced by the new offspring instead of replacing the worst element of whole population. This substitute makes sure that each member of the complex has at least one chance to develop before being removed or changed. As a result, no information in the community is disregarded.

B. Particle Swarm Optimization (PSO)

Particle swarm optimization algorithm is a population-based meta-heuristic motivated by memetic evolution. Eberhart and Kennedy (1995) created and developed PSO.

PSO is inspired by the simulation of swarm behavior; for instance, flocking behavior synchronicity is believed to be a product of birds' attempts to maintain an ideal distance from their surroundings. The particles (birds) modify their flying state depending on their own experience as well as the companions' experiences. The performance of each particle is measured according to a fitness function that is problem specific. The velocity and position of the particle is altered by the following equations[15].

$$V_id = WV_id + c_1 \text{ rand1}(P_id - X_id) + c_2 \text{ rand2}(P_gd - X_id), \quad d=1, \dots, D \quad (12)$$

$$X_id = X_id + V_id, \quad d=1, \dots, D \quad (13)$$

Where c_1 and c_2 are two positive constants, rand1 and rand2 are random numbers in the range $[0, 1]$. w is the inertia weight. The inertia weight w is used to manage how the history of previous velocities affects the current velocities.

C. SFLA Details and Mathematical Models

SFLA combines deterministic and stochastic techniques. The deterministic approach enables the algorithm to efficiently use response information to direct the heuristic search while the robustness and adaptability of the search pattern robustness are ensured by the random elements. We can summarize the algorithm as the following points:

- 1- When the search starts, a population of frogs cover the entire swamp is chosen randomly.
- 2- The population is divided into a number of memplexes that are free to evolve autonomously and explore in various directions by using PSO principles.
- 3- In each memplex, the frog is influenced by the ideas of other frogs, leading to memetic evolution.
- 4- To make the improvement process competitive, the frogs with best memes (ideas) must participate more to the creation of new memes than the others.
- 5- The memes of a frog may be changes by the memes of the best frog within the memplex or by the memes of the best frog of the population.
- 6- After a number of memetic, the emplexes are combine and new ones are formed by a process of shuffling. The memes' quality is improved by this shuffle after getting information from frogs of other areas of the swamp.

D. Mathematical Models: the following formulas represent the mathematical models of SFLA

- The total size of initial population is:

$$F = m * n \quad (14)$$

where m is the number of memplexes, n the number of frogs in each memplexes.

- The new position for the worst frog in memplex are calculated by:

$$X_new = X_w + S \quad (15)$$

Where X_w is the position of worst frog in same memplexes, S is the step size.

- The step size can be calculated as:

$$S = \min\{\text{int}[\text{rand}(X_B - X_w)], S_{max}\} \quad (16)$$

for positive step:

for negative step:

$$S = \min\{\text{int}[\text{rand}(X_B - X_W)], -S_{\max}\} \quad (17)$$

Where X_B is the position of the best frog in same memplex, S_{\max} maximum size of step.

• If the new position performance is not better than the old position performance, then the new position recalculate using global best position for positive step:

$$S = \min\{\text{int}[\text{rand}(X_G - X_W)], S_{\max}\} \quad (18)$$

for negative step:

$$S = \min\{\text{int}[\text{rand}(X_G - X_W)], -S_{\max}\} \quad (19)$$

Where X_G is the position of the best frog in entire population.

• If the new position which was calculated by the global best does not better than the old one too, so a new position will be selected randomly within the feasible search space.

IV. THE PROPOSED ALGORITHM

The proposed algorithm is a modified GWO. Grey wolves algorithm is combined with SFLA algorithm to get the best camera locations to take images to a specific suspicious object inside the human body.

The algorithm starts with the first steps of GWO and then moves to SFLA to identify the suspicious object in the body. After determining the position of this object, we return it to GWO, it will represent a prey, and the alpha, beta and alpha wolves will be determined with considering that position. The algorithm will continue for specific number of iterations and at the end it will return the best three positions for the camera to take images. These three image can give an accurate fused image of the object. The proposed algorithm consist of the following steps:

1. Initialize the camera positions.
2. Initialize a, A and C randomly.
3. Determine the object position by shuffled frog leaping algorithm.

- a. Initialize n and m, n is the n number of frogs in each memplex and m is the number of memplexes.
- b. Generate initial objects (population) randomly with size $m*n$.
- c. Calculate the fitness for each object by using predefined fitness function.
- d. Sort the objects according to the fitness
- e. Partition Population into m memplexes (U_k) $k=1,2,\dots,m$
- f. While $L \leq m$
- g. Sort the objects according to the fitness
- h. While $t < \text{No. of iterations}$
- i. Determine Best and Worst objects
- j. Calculate the step size by equation 16 or equation 17
- k. Find new object by equation 15 ($X_{\text{new}} = X_W + S$)
- l. Calculate the fitness value for the new object.
- m. If the new object fitness worse than worst fitness
- n. Calculate the step size by equation 18 or equation 19

- o. Find new object by equation 15
- p. Calculate the fitness value for the new object
- q. If the new object fitness worse than worst fitness
- r. Generate a new object randomly
- s. Replace Worst object
- t. Shuffle the memplexes
- u. Convergence criteria
- v. Determine the best solution
- w. Process the result and return it to GWO

4. Determine X_α , X_β and X_δ
5. While $T < \text{No. of iterations}$
6. Select new a, A and C randomly
7. Update each camera position
8. Update X_α , X_β and X_δ
9. Give best fusion output

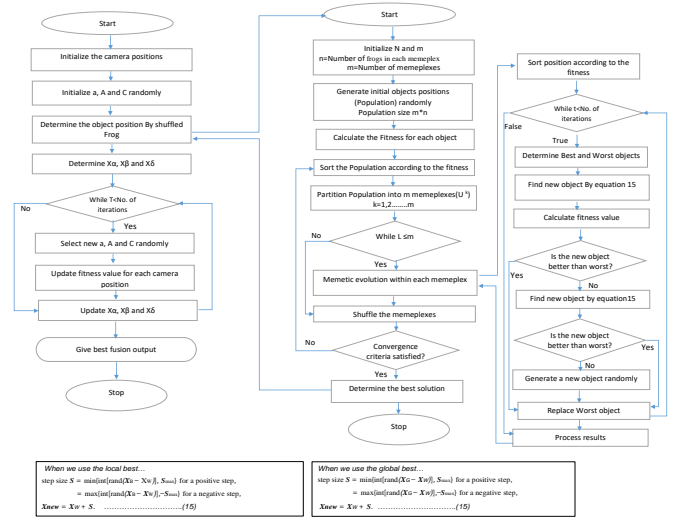


Fig. 2. Proposed Algorithm

V. RESULTS

We compared the results of our proposed algorithm with the results of GWO, Cuckoo Search algorithm and MGWO. The results are shown in Table 2. We used fixed-dimension multimodal benchmark functions shown in Table 1. The results showed that the performance of our algorithm is better than the other three algorithms.

TABLE 1. FIXED-DIMENSION MULTIMODAL BENCHMARK FUNCTIONS

Function	Range	Dim.
$F_1(x) = 4x_1^2 - 2.1x_1^4 + \frac{1}{3}x_1^6 + x_1x_2 - 4x_2^2 + 4x_2^4$	[-5,5]	2
$F_2(x) = (x_2 - \frac{5.1}{4\pi^2}x_1^2 + \frac{5}{\pi}x_1 - 6)^2 + 10(1 - \frac{1}{8\pi})\cos x_1 + 10$	[-5,5]	2
$F_3(x) = [1 + (x_1 + x_2 + 1)^2(19 - 14x_1 + 3x_1^2 - 14x_2 + 6x_1x_2 + 3x_2^2)] \times [30 + (2x_1 - 3x_2)^2 \times (18 - 32x_1 + 12x_1^2 + 48x_2 - 36x_1x_2 + 27x_2^2)]$	[-5,5]	2
$F_4(x) = \frac{1}{2} \sum_{i=1}^n (x_i^4 - 16x_i^2 + 5x_i)$	[-5,5]	2

TABLE 2. THE MINIMUM FITNESS OF THE ALGORITHMS

	GWO	Cuckoo Search	MGWO	Our algorithm
$F_1(x)$	-4.226811526972933	-1.990481998804186	-3.652210810063419	-4.801204328698046
$F_2(x)$	3.3175221040815135	6.555690951908623	4.289394062564477	3.0544760946469838
$F_3(x)$	4.274871884393374	45.6851776	32.685177664565806	3.021234306585737
$F_4(x)$	-74.11134344908257	-63.81311410656069	-66.4927461814071	-78.28833417541267

VI. CONCLUSION

This article proposes a new metaheuristic algorithm based on grey wolf algorithm.

To optimize image fusion, this suggested approach combines a number of optimization algorithms. The SFLA in the proposed algorithm is used to search the suspicious objects and direct the camera then GWO will search the best positions to tack images. This method accurately optimizes image fusion.

ACKNOWLEDGMENTS

The authors would like to thank the Iraqi Commission for Computer and Informatics, as well as the Informatics Institute for Post Grad, for their help and encouragement in performing this work.

REFERENCES

[1] Shehanaz, S., Daniel, E., Guntur, S. R., & Satrasupalli, S. (2021). Optimum weighted multimodal medical image fusion using particle swarm optimization. *Optik*, 231, 166413.

[2] Dutta, S., & Banerjee, A. (2020, March). Optimal image fusion algorithm using modified grey wolf optimization amalgamed with cuckoo search, levy fly and Mantegna algorithm. *2020 2nd International Conference on Innovative Mechanisms for Industry Applications (ICIMIA)* (pp. 284-290). IEEE.

[3] Al-Helali, A. H., Ali, H. A., Al-Dulaimi, B., Alzubaydi, D., & Mahmmoud, W. A. (2009). Slantlet transform for multispectral image fusion. *Journal of Computer Science*, 5(4), 263.

[4] Waheed, S. R., Suaib, N. M., Rahim, M. S. M., Adnan, M. M., & Salim, A. A. (2021, April). deep learning algorithms-based object detection and localization revisited. *Journal of Physics: Conference Series* (Vol. 1892, No. 1, p. 012001). IOP Publishing.

[5] Mahajan, S., Abualigah, L., Pandit, A. K., Al Nasar, M. R., Alkhazaleh, H. A., & Altalhi, M. (2022). Fusion of modern meta-heuristic optimization methods using arithmetic optimization algorithm for global optimization tasks. *Soft Computing*, 26(14), 6749-6763.

[6] Al-Jawher, W. A. (2007). New fast method for computing multiwavelet coefficients from 1D up to 3D. *Proc. 1st Int.*

Conference on Digital Comm. & Comp. App., Jordan (pp. 412-422).

[7] Al-Jouhar, W. A., & Abbas, T. M. (2006). Feature combination and mapping using multiwavelet transform. *Iraq Academic Scientific Journals*, 3(19), 13-34.

[8] Mahmoud, W. A., Abdulwahab, M. S., & Al-Taai, H. N. (2005). The determination of 3D multiwavelet transform.

[9] Al-Helali, A. H. M., Mahmmoud, W. A., & Ali, H. A. (2012). A Fast personal palmprint authentication Based on 3d-multi Wavelet Transformation. *International Journal of Scientific Knowledge*, 2(8).

[10] Mahmoud, W. A. (2011). A smart single matrix realization of fast walidlet transform. *International Journal of Research and Reviews in Computer Science*, 2(1), 144.

[11] Salim, A. A., Bakhtiar, H., & Ghoshal, S. K. (2021). Improved fluorescence quantum yield of nanosecond pulse laser ablation wavelength controlled cinnamon nanostructures grown in ethylene glycol medium. *Optik*, 244, 167575.

[12] Waheed, S. R., Rahim, M. S. M., Suaib, N. M., & Salim, A. A. (2023). CNN deep learning-based image to vector depiction. *Multimedia Tools and Applications*, 1-20.

[13] Al-Jadir, I., & Mahmoud, W. A. (2021). A grey wolf optimizer feature selection method and its effect on the performance of document classification problem. *Journal Port Science Research*, 4(2).

[14] Salim, A. A., Ghoshal, S. K., Shamsudin, M. S., Rosli, M. I., Aziz, M. S., & Harun, S. W. & Bakhtiar, H. (2021). Absorption, fluorescence and sensing quality of Rose Bengal dye-encapsulated cinnamon nanoparticles. *Sensors and Actuators A: Physical*, 332, 113055.

[15] Waheed, S. R., Alkawaz, M. H., Rehman, A., Almazyad, A. S., & Saba, T. (2016). Multifocus watermarking approach based on discrete cosine transform. *Microscopy Research and Technique*, 79(5), 431-437.

[16] Jubier, N. J., Hassani, R. H., Hathot, S. F., & Salim, A. A. (2023). A new type of carbonate hydroxyapatite nanoparticles made from PMMA and oyster shells: Evaluation of structure, morphology and biocompatible properties. *Polymer Bulletin*, 1-15.

[17] Waheed, S. R., Sakran, A. A., Rahim, M. S. M., Suaib, N. M., Najjar, F. H., Kadhim, K. A., ... & Adnan, M. M. (2023). Design a crime detection system based fog computing and IoT. *Malaysian Journal of Fundamental and Applied Sciences*, 19(3), 345-354.

[18] Waheed, S. R., Saadi, S. M., Rahim, M. S. M., Suaib, N. M., Najjar, F. H., Adnan, M. M., & Salim, A. A. (2023). Melanoma skin cancer classification based on CNN Deep learning algorithms. *Malaysian Journal of Fundamental and Applied Sciences*, 19(3), 299-305.

[19] Kadhim, K. A., Najjar, F. H., Waad, A. A., Al-Kharsan, I. H., Khudhair, Z. N., & Salim, A. A. (2023). Leukemia Classification using a Convolutional Neural Network of AML Images. *Malaysian Journal of Fundamental and Applied Sciences*, 19(3), 306-312.