Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 8, No. 4, 1026-1038
2024
Publisher: Learning Gate
DOI: 10.55214/25768484.v8i4.1479

Whale optimization algorithm based rigid and non-rigid registration

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Abstract: Image registration has become one of the most widely used transformation techniques in satellite and medical imaging nowadays is image registration. Mapping of two or more than two images are known as registration of images. Multimodal images are those that are processed using the same registration model but were taken with different devices. In the current work, we introduce a multimodal image registration framework on which we have applied two meta-heuristic algorithms: the Whale Optimization Algorithm (WOA) and Particle Swarm Optimization (PSO), to reduce processing time and enhance the performance of both rigid and non-rigid multimodal registration frameworks. The outcomes of WOA and PSO based framework has been compared with each other with respect to both rigid and non-rigid frameworks.

Keywords: *Image registration, Multimodal, Non-rigid registration, Particle swarm optimization (PSO), Rigid registration, Whale optimization algorithm (WOA).*

1. Introduction

A critical step in computer vision and medical imaging is image registration optimization. To allow for precise image data fusion, analysis, and comparison, it entails aligning two or more images. By determining the best transformation to project one image onto another, this alignment is accomplished. image registration plays a significant role in different applications, such as object recognition, picture stitching, 3D reconstruction, and image-guided treatments. However, because of things like geometric deformities, occlusions, and image noise, image registration is a difficult operation to accomplish accurately and efficiently. Numerous optimization [1] strategies have been developed to address these issues. With the use of these methods, the ideal transformation parameters [2] that reduce the disparity between the registered images [3] are sought after. Iteratively modifying the transformation parameters until an ideal solution is obtained is the optimization process. A popular technique for optimization is the gradient descent algorithm. The transformation parameters [4] are first estimated by this technique, which then iteratively updates them in the direction of the steepest descent. The gradient information is used to minimize the objective function, which calculates how different the images are from one another. The use of genetic algorithms is another well-liked optimization [5] strategy. This approach, which draws inspiration from biological evolution, applies genetic operations like crossover and mutation to a population of candidate solutions in order to evolve toward better answers. A similarity metric is used to assess each candidate solution's fitness, and the best solutions are chosen for the following generation.

In addition to these methods, particle swarm optimization [5] and simulated annealing are two further optimization techniques that have been used for image registration[6, 7]. Simulated annealing simulates the annealing process in metallurgy by gradually decreasing the search space, allowing the

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method to avoid local minima. Particle swarm optimization [8, 9], on the other hand, uses a model of particle motion in a search space to find the optimal solution. It is inspired by flocks of birds and their collaborative behavior. Advanced tactics that aid in enhancing image registration [10, 11] optimization include feature-based algorithms and multi-resolution techniques. Multi-resolution techniques perform registration at many image scales, from coarse to fine, to improve efficiency and accuracy. In order to direct the registration [12, 13] process, feature-based approaches concentrate on locating and matching distinguishing elements in the photos, such as corners or edges. Even with the improvements in optimization methods, image registration [14, 15] is still a topic of current research. Scholars are consistently investigating novel algorithms and tactics aimed at enhancing the precision, velocity, and resilience of the registration [16] procedure. A meta-heuristic optimization method inspired by nature that emulates humpback whale hunting behavior is the Whale Optimization [17, 18] Algorithm (WOA). The bubble-net hunting tactic served as the model for the algorithm. Humpback whales [19] use a foraging strategy known as the "bubble-net feeding method." Hunting near the surface for schools [20] of krill or small fish is what humpback whales prefer to do. It has been noted that this foraging is carried out by blowing characteristic bubbles in a path that forms a circle or a "9." The exclusive activity of bubble-net feeding is exclusive to humpback whales. The spiral bubble-net feeding maneuver is theoretically described in the whale optimization algorithm (WOA) to carry out optimization.

- WOA mimicked hunting activities by using either a random or optimal search agent to pursue the target.
- WOA mimics the humpback whales' bubble-net attacking technique with a spiral.

The development of deep learning techniques has produced encouraging outcomes in the field of image registration, where convolutional neural networks are utilized to determine the best transformation straight from the image data [21]. A crucial challenge in computer vision and medical imaging is optimizing image registration. Accurate image alignment can be accomplished by applying a variety of optimization approaches, including particle swarm optimization, simulated annealing, gradient descent, and genetic algorithms. Moreover, the registration process can be improved by utilizing feature-based and multi-resolution techniques. The capabilities of image registration will be further enhanced by ongoing research and development in this area, enabling more precise analysis and interpretation of image data.

The current work aims to reduce the image registration's processing time using optimization framework of whale optimization [22, 23] algorithm. The key objective of this study is to increase the registered image's quality by optimizing the framework and reducing the image registration error. The framework uses both rigid and non-rigid registration on multimodal framework. The study is compared with the results of particle swarm optimization-based framework. In the next section related literature is presented. Section 3 discusses different methodologies and materials used in the study; proposed framework is discussed in section 4. The obtained results are presented in section 5 and paper concludes in section 6.

2. Literature Review

Nonrigid registration with free-form deformations [25] was introduced by Rueckert et al in 1999. They presented a novel method in this study for the nonrigid registration of breast MRI augmented with contrast. A model of the movements of the breast that follows a hierarchical change has been created. Mutual information-based rigid and nonrigid ultrasound volume registration [26] was introduced by Shekhar et al. in 2002. The method used in this research to register ultrasound volumes based on mutual information measure was first used for multimodality registration of brain pictures. Different rigid and affine transformation-based registration that involved increasingly generalized transformations were examined in this work. Distortion correction was achieved by Gholipour et al. by the non-rigid registration of functional to anatomical magnetic resonance brain imaging [27]. This study offered a non-rigid registration method based on the mutual information similarity measure and the B-spline free-form deformation model. A robust and speedy registration was accomplished by developing an optimization approach. Unlike the preceding formulations, this one uses a second-order optimization algorithm with restricted memory, as opposed to the typical first-order gradient-based techniques. Robust non-rigid point set registration [28] based on dynamic tree was proposed by Qu et al. This article explored an innovative approach using dynamic trees to handle the challenging problem of non-rigid registration of point sets with considerable shape difference, which has proven to be a challenge for current methods. After determining the degree of similarity between two-point sets using the Affine ICP algorithm with bidirectional distance, non-rigid registration was carried out on subjects and models that were comparable. Through the use of enhanced affine transformation and gaussian weighted shape context, non-rigid [29] registration was introduced by Min et al. for visible and infrared images. This work proposed a point feature-based method to improve the non-rigid IR and VIS image registration performance. A feature descriptor known as Gaussian weighted shape context (GWSC) is enhanced from shape context (SC) in order to rapidly extract matching point pairs from edge maps in visible and infrared images.

Mirjalili and Lewis first introduced whale optimization algorithm (WOA) [18] in 2011. The Whale Optimization Algorithm (WOA) is a novel meta-heuristic optimization algorithm that draws inspiration from nature and mimics the social behavior of humpback whales, was proposed in this study. The bubble-net hunting tactic served as the algorithm's inspiration. Six structural design challenges and 29 mathematical optimization tasks were used to test WOA. The optimization results demonstrate how competitive the WOA algorithm was when compared to both traditional approaches and the most advanced meta-heuristic algorithms. In 2019 the development of a hybrid whale optimization [30] technique was done by Tang et al. The hybrid modified whale optimization algorithm (HIWOA), which was introduced in this study, included a new feedback mechanism to increase population diversity and lower the likelihood of local optimization. The updating of each whale's unique position was made better by the application of the nonlinear convergence factor and the inertia weight coefficient, which also increased convergence speed and accuracy. To increase the performance of object searching, Cheng and Guo (2021) presented a whale optimization approach [31] based on a speed-up robust feature. The authors of this study developed an object search method, which has the advantages of various search methods and fast convergence. The whale optimization algorithm, which takes over the previous global best value (IGP-WOA), served as its foundation.

Significant work has been done in the domain of rigid and non-rigid image registration and whale optimization algorithm but none of the work managed to put these two algorithms or techniques together to optimize the image registration framework. The current work aims to solve this issue.

3. Materials and Methods

3.1. Whale Optimization Algorithm (WOA)

The largest mammal in the entire animal kingdom, whales [17, 18], are magnificent creatures. This animal has several key sections, including the humpback, killer, blue, and finback. Because they must breathe in the seas and oceans most of the time, whales never sleep. Furthermore, only half of brains are capable of sleep. Wales people [19, 20] either live alone or in communities. Certain species, like killer whales, can spend the majority of their lives as a family. Small fish and krill species are the preferred prey of humpback [21, 22] whales, who are thought to be the largest whale species. Whales have basic cells in certain areas of their brains. Human behavior, emotions, and judgment are all controlled [23 ,24] by these cells. However, whales vary from humans in that they have twice as many of these cells, which is the primary source of their intelligence. Whales have low-level human-like behavior; they are capable of learning, thinking, communicating, feeling emotions, and even developing a dialect. The primary attraction of humpback whales is thought to be their unique hunting strategy, which is known as the bubble-net feeding method. The WOA assumes that the target prey is the best possible candidate solution. This formula explains how the whales encircle their prey.

$$Di = \left| C\overrightarrow{Y^*}(t) - Y(t) \right| \quad (1)$$

$$Y(t+1) = \overrightarrow{Y^*}(t) - \vec{A}.\overrightarrow{Di} \quad (2)$$

where t alludes to the iteration of the present place, A and C are coefficient vectors. $\overrightarrow{Y^*}$ is the the current optimal solution's location [18] vector, $\vec{Y}$ is the position vector. The vectors $\vec{A}$ and $\vec{C}$ is calculated using the following equations:

$$\vec{A} = 2.\vec{a}.\vec{s} - \vec{a} \quad (3)$$

$$\vec{C} = 2.\vec{s} \quad (4)$$

where $\vec{a}$ can be chosen during the iterations between 2 and 0, and $\vec{s}$ is a random vector in the range [0, 1]. The humpback whales are employing the bubble-net technique to assault their prey in this instance. According to the following scenario, this algorithm uses two ways to explain the mathematical model of the humpback whales' bubble-net phase: (i) The shrinking encircling technique allows to lower the value of $\vec{a}$ in Eq. (3) and $\vec{A}$ is selected randomly in the range of $[-\vec{a}, \vec{a}]$ such that $\vec{a}$ can be lowered over the iterations from 2 to 0. (ii) The spiral updating position method uses the following equation to evaluate a spiral equation for the position of the whale and prey:

$$\vec{Y}(t+1) = \overrightarrow{Di}.e^{bi}\cos(2\pi l) + \overrightarrow{Y^*}(t) \quad (5)$$

where $\overrightarrow{Di} = \left| \overrightarrow{Y^*}(t) - \vec{Y}(t) \right|$ specifies the distance between the i^{th} whale and prey, b is a constant, and l is a random number in the range [−1, 1]. In the optimization stage, humpback [18] whales swim in a decreasing circle around their prey, with a 0.5 percent chance of selecting the shrinking encircling mechanism or the spiral model to update their position. Consequently, the following equation can be used to explain the mathematical model of this behavior:

$$\vec{Y}(t+1) = \begin{Bmatrix} \overrightarrow{Y^*}(t) - \vec{A}.\overrightarrow{Di} & if \quad p < 0.5 \\ \overrightarrow{Di}.e^{bi}\cos(2\pi l) + \overrightarrow{Y^*}(t) & if \quad p \geq 0.5 \end{Bmatrix} \quad (6)$$

where p is defined as a random value in the interval of [0,1].

A is defined in this phase by a random number between 1 and − 1. Assume that A>1 in order for this global search algorithm to function. The following formulas can be used to represent this mechanism in mathematics.

$$\overrightarrow{Di} = \left| \vec{C}.Y_{rand} - \vec{Y} \right| \quad (7)$$

$$\vec{Y}(t+1) = \vec{Y}_{rand}(t) - \vec{A}.\vec{D} \quad (8)$$

where Y_{rand} is described as a vector of random positions. Starting the search process with a few randomly chosen solutions is how the WOA [29, 30] algorithm operates. Every iteration, the search agents update their positions [31] at random by selecting the search agents who haven't yet been found. The parameter has values between 2 and 0. When A>1, the random search agent is chosen.

3.2. Image Registration Frameworks

In order to align two or more photos, an approach known as "transformation-based image registration" includes calculating and applying transformation parameters. Translation, rotation, scaling, shearing, and non-linear deformations [7] are some examples of this transformation. In order to enable precise spatial alignment, it seeks to reduce the discrepancies between corresponding features in the images.

3.2.1. Rigid Registration

The procedure of rigid registration entails aligning two or more photographs, usually of a medical nature, in order to create a spatial relationship between them. It is essential to many medical applications, including radiation therapy, diagnostic imaging, and image-guided surgery. Accurate picture alignment, guaranteeing related anatomical structures [7] are in the same spatial positions, is the aim of rigid registration. The term "rigid" describes the presumption that there is no non-linear warping or deformation and that the only possible transformations between the images are translation, rotation, and scaling. This supposition streamlines the registration procedure [11], increasing its computational efficiency and reducing the likelihood of errors. In order to determine the transformation parameters that would best align the images, rigid registration uses mathematical algorithms and optimization techniques. These algorithms estimate the degree of correspondence between the images using a variety of similarity metrics, including mutual information and sum of squared differences. Rigid registration [13] has a wide range of uses. Surgeons can use image-guided surgery to superimpose preoperative photographs on the patient's anatomy and receive real-time direction while the surgery is being performed. It guarantees precise tumor targeting in radiation therapy, reducing harm to healthy tissues. It helps with illness diagnosis and monitoring in diagnostic imaging by enabling the comparison of images taken at various times. In the realm of medical imaging, rigid registration is an essential instrument that helps with accurate picture alignment and integration for better research, diagnosis, and therapy.

3.2.1. Non-Rigid Affine Registration

Affine registration is a potent image processing method that applies a more flexible transformation than rigid registration to align two or more images. Unlike rigid registration, affine registration [2] allows for not only translation, rotation, and scaling but also shearing [4] and non-uniform scaling. With this extra flexibility, pictures with different anatomical structures and deformations can be aligned more accurately. An "affine" mathematical transformation [6] is one that maintains ratios of distances between points and parallel lines. Shearing, translation, rotation, and scaling parameters can all be included in a matrix to express an Affine transformation. Affine registration [10] optimizes the spatial alignment of the images by minimizing the differences between matching features [11, 12] through the adjustment of these parameters. Applications for Affine Registration can be found in computer vision, remote sensing, and medical imaging, among other areas. It is especially helpful in medical imaging [15] when matching images taken at different times or with different modalities. For instance, affine registration in brain imaging can help with surgical outcome assessment by aligning preoperative and postoperative magnetic resonance images.

Using optimization algorithms, the transformation parameters are estimated throughout the affine registration process. Typically, these methods estimate the similarity [16] between relevant features in the images using similarity measures like mutual information or normalized cross-correlation. The program looks for the best alignment that minimizes [25] the differences between the images by iteratively modifying the transformation parameters. Affine registration is a flexible method that improves the precision and dependability of picture interpretation and analysis. Its capacity to manage intricate changes makes it a priceless instrument in a wide range of scientific and medical applications, advancing investigation, diagnosis, and therapy.

3.2.3. Monomodal and Multimodal Registration

There are two primary categories of image registration [26] frameworks: multimodal and monomodal. Aligning images obtained using the same imaging modality is known as monomodal image registration. It can entail, for instance, aligning several computed tomography (CT) scans or magnetic resonance imaging (MRI) images of the same patient. Accurate picture alignment is the aim of monomodal registration, which facilitates the viewing of intricate anatomical characteristics and enhances the ability to compare structures over time. Multimodal image registration, on the other hand, focuses on aligning [27] images obtained using various imaging modalities. This can entail matching an MRI to a CT scan or a PET scan to an MRI. Multimodal registration is more challenging due to the differences in image intensity, contrast, and spatial resolution between the modalities. Establishing a meaningful spatial relationship between the pictures is the goal of multimodal registration. This will allow complementary information to be fused and enable more accurate diagnosis, treatment planning, or image-guided actions. To determine the transformation parameters that will best align [28] the images, both monomodal and multimodal image registration rely on mathematical algorithms and optimization techniques. These techniques estimate the degree of correspondence between the images using a variety of similarity measures, such as mutual information or correlation coefficients. Whereas multimodal image registration [21] works with aligning images from many modalities, monomodal image registration concentrates on aligning images from the same modality. Both kinds of registration have significant uses in many different domains, enhancing image analysis, diagnosis, and treatment planning. Multimodal framework is used in the current work..

4. Proposed Method

The multimodal images in the ROCO dataset [21] were initially sourced from the aforementioned database, as depicted in Figure 1. Selected multimodal images were sent to the framework. For the multimodal [2] framework, both rigid and non-rigid affine transformation were required during the registration procedure. The optimization method is implemented using the meta-heuristic algorithms in the registration framework.

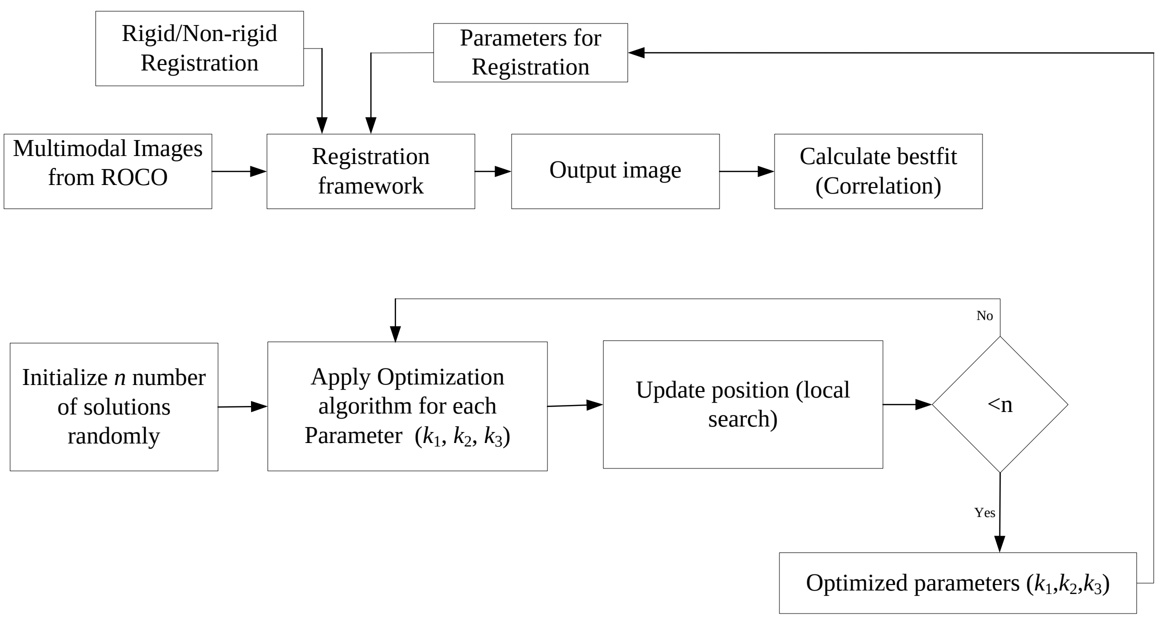


Figure 1.
Block diagram of the proposed framework.

In the current work, Whale Optimization algorithm has been used and it has been compared with Particle Swarm Optimization. Initial Radius [4], Epsilon, and Growth Factor [7] of the Rigid and Affine transformation have been employed as scaling variables in the current work. Table 1 below displays the scaling factor values.

Table 1.
Values of the scaling factors.

Image registration frameworks	Rotational radius	Epsilon value	Growth factor for scaling
Rigid	9×10^{-3}	1.59×10^{-4}	1.01
Affine	9×10^{-3}	1.59×10^{-4}	1.01

Whale optimization algorithm based image registration (Pseudocode)
Initialize number of whales (Υ_i)
Initialize reference and target image
Evaluate fitness (correlation) of every whale
while (i<max_iter)
for whale $t=1{:}i$:
update a, A, C, l, p,
if $p<0.5$:
if ($|A|<1$):
Update whale using eq. (1)
Apply image registration framework
else:
Select whale randomly: Υ_{rand}
update whale using eq (8)
Apply image registration framework with updated whale
else:
update whale by eq (5)
end-for
Verify whether any whale goes beyond search-space, then modify it
Calculate whale's fitness (correlation)
Update Υ_{best}
if better solution found:
$i = i+1$
end-while
return Υ_{best}
return Registered image for Υ_{best}

5. Experimental Results

5.1. Dataset

The ROCO [21] dataset is the one that was used for this experiment. In COntext (ROCO), the term "ROCO" refers to Radiology Objects [21]. There are a lot of multimodal medical photos in this dataset. The dataset has been applied to both image classification and generative models for captioning images. A part of the ROCO dataset has been made available for concept detection tasks at ImageCLEF 2019 [21].

5.2. Analysis

The current work was tested and implemented using a machine with a Ryzen 5 3.2 GHz processor and MatLab R2018a for the Particle Swarm Optimization, Whale Optimization Algorithm, and image registration. The lungs' multimodal pictures from a pectus excavatum patient's computed tomography (CT) image were selected for the current image registration framework from the ROCO Dataset. The correlation coefficient between the original and final image served as the performance evaluation parameter. [28] computes the correlation coefficient.

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 8, No. 4: 1026-1038, 2024
DOI: 10.55214/25768484.v8i4.1479

$$correlation = \frac{\sum_a \sum_b (\text{Img1}_{ab} - \text{Img1}^{'})(\text{Img2}_{ab} - \text{Img2}^{'})}{\sqrt{(\sum_a \sum_b (\text{Img1}_{ab} - \text{Img1}^{'})^2)(\sum_a \sum_b (\text{Img2}_{ab} - \text{Img2}^{'})^2)}} \tag{9}$$

In WOA based and PSO based frameworks, population were fixed at 15. The evaluation metrics and the three parameters that were to be optimized for the rigid multimodal registration framework based on WOA—k_1, k_2, and k_3—are provided in Table 2.

Table 2.
Whale optimization algorithm based rigid registration.

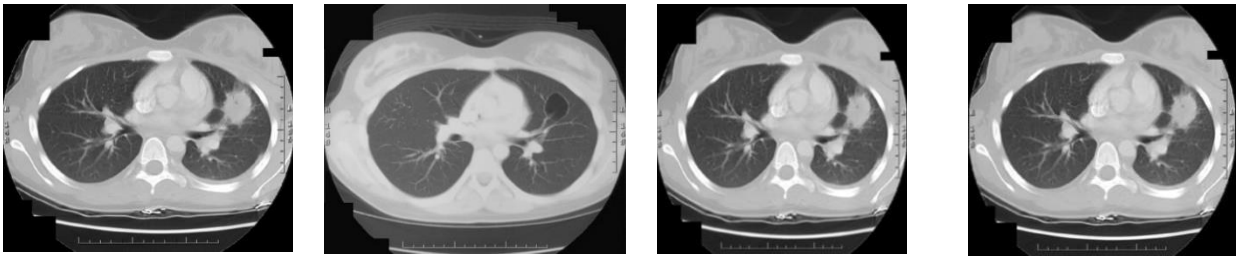
Iterations	k_1	k_2	k_3	Best fitness (Correlation)	Processing time (Seconds)
5	20	21	20	0.7576	981.74
10	31	43	22	0.7595	1332.81
15	54	87	75	0.7841	1865.56
20	98	98	92	0.8781	2742.31
25	98	98	92	0.8781	3415.65

Table 2 shows that as a result of whale optimization algorithm based rigid registration framework, the optimal value was obtained after 20th generation at best fitness value of 0.8781 which was the correlation between reference and registered image establishing that the registration error is significantly low.

Table 3.
Whale optimization algorithm based non-rigid affine registration.

Iterations	k_1	k_2	k_3	Best fitness (Correlation)	Processing time (Seconds)
5	31	21	41	0.7550	952.03
10	41	61	28	0.7411	1505.93
15	86	88	86	0.9042	2122.15
20	98	98	98	0.9184	2732.71
25	98	98	98	0.9184	3411.27

Table 3 shows the obtained optimization values on non-rigid affine registration when Whale Optimization Algorithm (WOA) is applied. The current framework optimized after 20th iteration and managed to achieve even better correlation than rigid registration framework with 0.9184 value. This means the registration error between registered and the reference image is very low. The obtained images from Whale optimization based rigid and non-rigid registration framework are shown below. The 4th image in the image matrix clearly shows that the optimization framework has significantly improved the quality of the obtained image.



Original image | Reference image | WOA based rigid registered image | WOA based non-rigid registered image

Figure 2.
Original, Reference, Rigid registered and non-rigid registered images.

The current framework was compared with PSO based rigid and non-rigid registration. The obtained results of rigid framework are shown in Table 4. Table 4 reports that the registration error was high with a low optimal fitness of 0.7731.

Table 4.
Optimized rigid registration using PSO.

Iterations	k_1	k_2	k_3	Best fitness (Correlation)	Processing time (Seconds)
5	71	49	74	0.7174	811.61
10	42	91	96	0.7596	1674.27
15	75	85	91	0.7623	2451.26
20	90	90	90	0.7731	3674.45
25	90	90	90	0.7731	4225.51

The PSO-based non-rigid registration framework was tested and the results are demonstrated in table 5 which shows a significant improvement of correlation, although it was comparatively low than WOA based framework.

Table 5.
Optimized non-rigid affine registration using PSO.

Iterations	k_1	k_2	k_3	Best fitness (Correlation)	Processing time (Seconds)
5	21	20	20	0.7427	794.46
10	35	25	48	0.7490	1739.18
15	71	94	46	0.8785	2501.59
20	88	88	88	0.9058	3475.88
25	88	88	88	0.9058	4132.54

The WOA based Rigid and non-rigid affine framework was compared with the PSO based Rigid and Non-rigid framework. Firstly, the fitness analysis shows that a major improvement has happened as a result of WOA based Non-rigid registration which outperformed other frameworks in terms of optimal fitness, which was the correlation between registered and reference image.

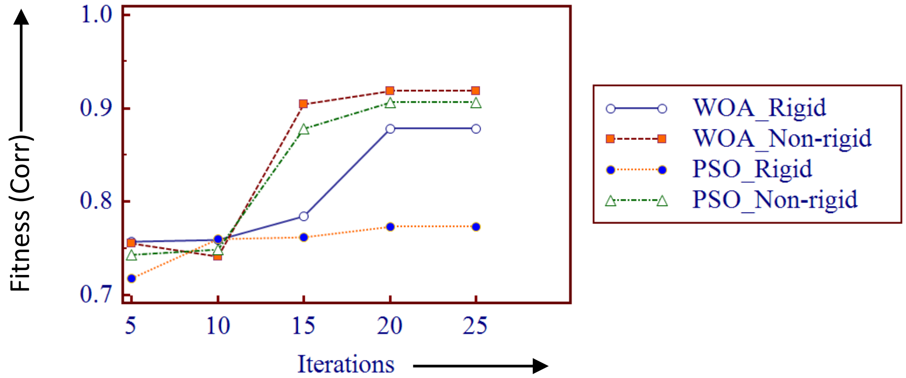


Figure 3.
Comparative analysis of optimal fitness of different frameworks.

WOA based Rigid and Non-rigid registration frameworks were faster than PSO [8, 9] based registration. The WOA based rigid took the least time to converge and obtain the optimal fitness in this comparative analysis. The optimization frameworks overall shows that WOA based rigid registration framework was relatively faster than PSO based framework, but in terms of image quality, WOA [17] based non-rigid registration managed to achieve the least registration error.

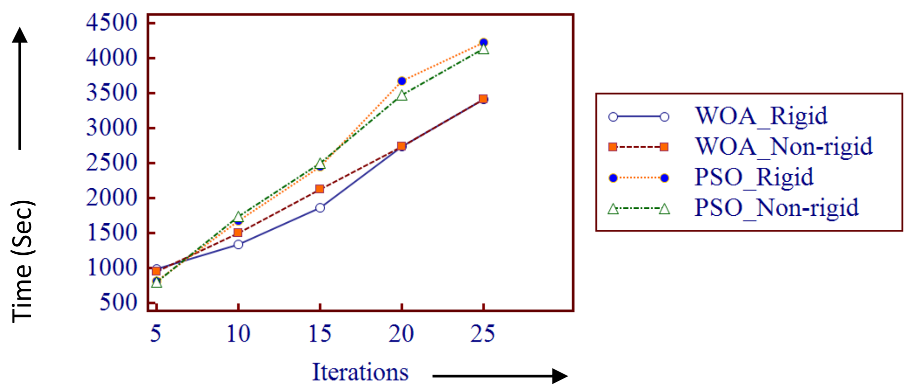


Figure 4.
Time complexity analysis.

WOA has demonstrated benefits like ease of use, quick convergence, and a sensible ratio of exploration to exploitation. It features an easy-to-use interface and has been developed in other computer languages.

6. Discussion

Figure 3, 4 and Table 4, 5 clearly indicates that using Whale Optimization algorithm on both rigid and non-rigid affine managed to enhance the quality of the image registration procedure. Figure 4 clearly indicates that the proposed framework even outperformed existing PSO-based registration in terms of time complexity.

The WOA method is a useful tool for optimization tasks in various industries because it has shown encouraging results in terms of accuracy and efficiency. Two evolutionary optimization techniques that have been used for image registration tasks are Whale Optimization Algorithm [18] (WOA) and Particle Swarm Optimization [14] (PSO). When compared to conventional optimization techniques, WOA and PSO have both been successfully used to address picture registration issues, increasing convergence time and alignment accuracy. However, the specifics of the photos and the optimization settings applied can affect how well these algorithms perform. Overall, the analysis showed that WOA was relatively faster and better performing than PSO based framework in terms of speed and accuracy.

The objective of the current work was to enhance rigid as well as non-rigid registration, in order to achieve that the proposed framework used whale optimization to optimize the parameters of rigid and non-rigid affine registration. As the image registration process often deals with registration errors and it also takes a lot of time to process huge number of image frames, the prime objective of the work was to enhance the registered image and reduce the time complexity which will benefit the image registration process when applied into important domains such as medical imaging or satellite image.

7. Conclusions

In order to guarantee precise alignment of pictures and allow for insightful analysis and interpretation, image registration optimization is required. It helps reduce disparities between related features, improves spatial precision, and boosts the quality of fused or registered pictures. Applications including computer vision tasks, remote sensing, image-guided interventions, and medical diagnosis benefit from optimization's increased dependability and efficacy. Because of its quick convergence, resilience when dealing with non-linear deformations, and ability to strike a fair balance between exploration and exploitation, the Whale Optimization Algorithm (WOA) is frequently selected for optimization problems. Its capacity to imitate humpback whale social behavior makes it a desirable option for picture registration among other fields. Particle Swarm Optimization (PSO) and Whale Optimization technique (WOA) can be compared; each technique has advantages and disadvantages. WOA shows a better balance between exploration and exploitation as well as faster convergence. Additionally, it demonstrates resistance against non-linear deformations. It is imperative to assess both algorithms individually because their efficacy is contingent upon the particular challenge and its attributes. Frameworks based on Particle Swarm Optimization (PSO) are frequently used for benchmarking because of their ease of use and capacity for rapid search space exploration. PSO is a useful tool for comparing and evaluating the efficacy of various techniques since it offers a benchmark for examining the performance of other optimization algorithms. The current study aimed at optimizing image registration frameworks both rigid and non-rigid. The current work used multimodal registration. The obtained results showed with the help of Whale Optimization Algorithm the framework managed to increase the rigid and non-rigid registration's accuracy and reduce the time complexity of both of these frameworks. The WOA based rigid registration managed to achieve a correlation of 0.9184 and non-rigid affine registration achieved correlation of 0.8781, while existing PSO based rigid registration obtained correlation of 0.7731 between original and registered image and non-rigid affine registration managed to achieve correlation of 0.9058. Hence in terms of improvement in registered image, WOA based registration was superior than existing PSO based method in both rigid and non-rigid frameworks. Table 2, 3, 4 and 5 also showed that WOA based rigid and non-rigid registration were faster than existing PSO-based registration methods. With the current parameter values obtained by WOA based rigid and non-rigid registration it should enhance the existing registration methods while applying into huge image database as it managed to reduce the registration error and reduce the execution time for registration per frame. The current work didn't include complex transformations like b-splines, demons etc. Feature based, intensity-based registration wasn't considered either, which may be included in future. Future work may also include other optimization algorithm and a comparative study on monomodal and multimodal frameworks as well.

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ISSN: 2576-8484
Vol. 8, No. 4: 1026-1038, 2024
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