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Unimodal Medical Image Registration using Elite Opposition Bacterial Foraging Optimization Algorithm

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ABSTRACT
Medical imaging applications frequently use image registration for a variety of purposes, and the search of an ideal image transformation parameters that align the two images (reference and floating) is still an optimization challenge. Medical image registration has been optimized using different metaheuristics optimization strategies. One method, the Bacterial Foraging Algorithm (BFOA), has issues of poor exploration and low convergence to a better solution. This research work presents the Elite Opposition Bacterial Foraging Optimization Algorithm (EOBFOA) for optimizing unimodal medical image registration. The EOBFOA is an enhanced version of Bacterial Foraging Algorithm (BFOA) using the Elite Opposition Strategy. The proposed EOBFOA uses Root Mean Square Error (RMSE) as a measure to determine the accuracy of the image registration process. The performance of the image registration using the EOBFOA was compared against other existing nature inspired algorithms. The obtained results shown that the proposed EOBFOA outperformed other algorithms in searching for the best optimum transformation parameters for the image registration.

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INTRODUCTION

The registration of image sequences problem, which dates back to the 1980s, is frequently encountered in a number of industries, including remote sensing, optical imaging, medical image analysis, satellite imaging, and others (Charif et al., 2019). Image registration (IR) is one of the most important image analysis methods in medical imaging. It has many applications; such as, matching various images token at different moments of same object or captured using different medical imaging types, e.g., computer tomography, magnetic resonance imaging, ultrasound, and X-ray (Alkinani, 2021.). Medical image registration is a procedure that optimizes the application of various geometric transformations to one or more moving images in order to match their spatial pose with that of a target image, establishing a connection between them. In order to do this, moving and target images must include some anatomical components that are expected to lay in a comparable place and orientation following the registration procedure (Andrade et al., 2019).

The methods for registering images that are now used fall mostly into two categories: geometric and iconic registration. In the geometric registration, the extracted points, edges, and surfaces from both images are used to determine how closely the features matchup. These primitives should be simple to detect and resistant to a variety of acquisition process alterations in order to achieve registration with high accuracy. The values of the pixels are utilized to repeatedly calculate a transformation between the two images while optimizing some similarity measure in the iconic registration or intensity-based registration. (Charif et al., 2019).

Three levels of image registration can be applied to image registration. These three concepts are a transformation model, a similarity measure, and an optimization technique. The foundation of this method is the computation of a spatial transformation function between two images,

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which is followed by the superimposition of the two images on the best possible basis of their similarity. A stiff, affine, perspective, and curve (elastic) transformation model is used to simulate geometric shapes in the transformation form. An optimization process is created to discover the best transformation parameters, and a searching method is used to find the best values. (Dida et al., 2020).

The IR problem solving consists of approximating the parameters of a geometric transform which has to be applied to a source image in order to overlay it accordingly on the model image. Because the two images are subject of geometric transforms which approximate the pixels values, and more, the images can be obtained from different sources or in different illumination conditions, a perfect overlay which ensures a perfect match of the pixels values can't be obtained (Bejinariu et al., 2019). In the world of optimization, traditional optimization methods have been applied in finding the best solution around a specific domain, however the traditional methods (gradient base methods) experience difficulties in finding global optimum(Abiyev & Tunay, 2016; Imam *et al*., 2019). Technically, optimization algorithms can be classified into deterministic and stochastic optimization methods. The deterministic algorithms usually have better solution for a particular optimization problem when the same set of initial values are use at the initial stage of the algorithms. However, such method usually engaged in local search process and easily trapped in local optima. The stochastic optimization methods mostly use a random search process that can enable it escape from local optima and search for a good solution after certain number of iterations (Zhang et al., 2016). The optimization procedures can be more or less complex depending on: the complexity of functions to optimize, their number, the size of the problem domain and required precision. The complex optimization problems can be solved faster by means of the nature inspired algorithms which were developed in the last decade. They model the behavior of some species of living beings to find food, to avoid dangers or to perpetuate their species (Bejinariu & Luca, 2016).

Bacterial Foraging Optimization Algorithm (BFOA)

In 2002, Passion was inspired by the foraging behaviour of Escherichia Coli, and propose the Bacteria Foraging Optimization Algorithm (BFOA). The field of BFOA at present has attracted the attention of different researchers' in solving global optimization problem (Li, 2014). The BFOA based on social behaviour of the E.Coli bacterial has gain popularity and wider application in solving optimization problem ranging from robot coordination, distributed optimization and control (Singh, 2014). One of the key issues with BFOA is that, in comparison to other evolutionary algorithms like Genetic Algorithm (GA) and Differential Evolution, it has low convergence capabilities over multimodal and rough fitness applications (Sasithradri et al., 2014).

The Bacterial Foraging Optimization Algorithms is governed by four processes, which are chemotaxis, swarming, reproduction, elimination and dispersal. The chemotaxis process simulates the foraging behavior of bacteria through two operations: flip and swim. Specifically, the change in the solution that occurs when the bacteria move one step in a certain direction can be expressed as equation (1).

$$X(i,j+1,k,l) = X(i,j,k,l) + C(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i).\Delta(i)}} \qquad (1)$$

Where $X(i,j,k,l)$ is the position of ith bacterium in jth chemotaxis, the kth reproduction. The $\frac{\Delta(i)}{\sqrt{\Delta^T(i).\Delta(i)}}$ refers to the n-dimensional unit vector obtained by vector unit. It indicates the direction of foraging determined by bacteria. $C(i)$ is the moving step size of bacteria i. The objective function value of the bacterium at $X(i,j,k,l)$ is expressed as $f(X(i,j,k,l))$. When $f(X(i,j,k,l)) > f(X(i,j+1,k,l))$ (Chen et al., 2020)

The swarming behavior of the bacteria can be characterized by attraction and repulsion. The numerical relationship is defined in equation (2)

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$$J_{cc}(P_i) = \sum_{i=1}^{s}\left[-d_{att}\exp(-w_{att}\sum_{m=1}^{p}(P_{i,m} - \overline{P_m})^2)\right] + \sum_{i=1}^{s}\left[h_{rep}\exp(-w_{rep}\sum_{m=1}^{p}(P_{i,m} - \overline{P_m})^2\right] \quad (2)$$

Where d_{att} indicates the depth at which the attracted material is released by the ith bacterium, while w_{att} indicates the width of the attracted material (Chen et al., 2020).

In the reproduction stage, the bacteria reproduce in a better nutrient environment. The completion of chemotaxis and swarming is followed by reproduction. In this process also, the fitness of the bacteria is calculated and sorted. The ith bacterium is shown in equation (3).

$$J_{i,healt} = \sum_{j=1}^{Nc} J_i(j,k,l) \quad (3)$$

Thus, bacteria with high accumulated fitness values are unhealthy and have no chance to reproduce. The accumulated fitness values of bacteria are sorted in ascending order, and the first half of bacteria are chosen to generate another half of bacteria at the same positions to keep the population size (Guo et al., 2021).

In elimination and dispersal, some bacteria die because of the adverse environment, e.g. rising of the temperature may kill a group of bacteria in a certain range. This process is simulated by the dispersal of some bacteria with a small probability(Ped) Simultaneously, some new bacteria are randomly generated for replacement (Chen et al., 2017).

Elite Opposition Bacterial Foraging Optimization Algorithm

The Elite Opposition Strategy is a technique in the field of intelligence computation. Furthermore, its model and procedure with BFOA can be described as follows:

Let $X_i^e = (x_{i,1}^e, x_{i,2}^e, \ldots, x_{i,D}^e)\ i = 1,2, \ldots NP$ be an indiidual in the current , and its corresponding elite opposition solution $\breve{X}\,_{i,j}^{\,e}$ is defined as follows

$$\breve{x}\,_{i,j}^{\,e} = k.\left(da_j + db_j\right) - x_{i,j}^e \quad (4)$$

Where $k \in U(0,1)$ is a generalized coefficient , and it can be used to control the magnitude of opposition. $x_{i,j}^e \in [a_j, b_j]$, a_j and b_j are the predifined of search area, da_j and db_j are the dynamic boundaries defined as follows.

$$da_j = \min(X_{i,j}),\ \ db_j = max(X_{i,j}) \quad (5)$$

For a given problem, however, it possible that the transformed candidate may jump out of the box-constraint $[a_j, b_j]$, which implies that EOBL fails to transform a candidate into a valid one. To avoid this case, the transformed candidate is assigned to a random value within $[a_j, b_j]$, as follows.

$$\breve{x}\,_{i,j}^{\,e} = rand(a_j, b_j), \text{ if } \breve{x}\,_{i,j}^{\,e} < a_j \,\|\breve{x}\,_{i,j}^{\,e} > b_j \quad (6)$$

Where $rand(.)$ is a random number in $[a_j, b_j]$.

	Elite Opposition Bacteria Foraging Optimisation Algorithm
Step 1	initialization
	Setting parameters:$S, N_s, N_c, N_{re}, P_{ed}$
	$Let\ j = k = l = 0\ (three\ loop\ indicators)$
	$Initialize\ the\ population\ of\ the\ bacteria$
	Generate the elite opposition based bacteria population using equation (4)
	$\boldsymbol{Update\ the\ dynamic\ interval\ boundaries\ [a_j, b_j]\ according\ to\ equation\ (5)}$
Step 2	$Elimination - dispersal$ loop *l=l+1*
Step 3	$Reproduction\ loop$ *k=k+1*
Step 4	$Chemotaxis\ loop\ j = j + 1$

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Step 5 *Each of the bacteria* $i = 1,2,..S$ *take chemptatic step for bacterium i as follows*

$a\ compute\quad f(X(i,j,k,l)$

$b\ compute\quad f_{last} = f(X^e(i,j,k,l)$

If $f_{last} < f(X(i,j,k,l)$,

If $\boldsymbol{f_{last}} < \boldsymbol{f(X^{best})}$, **let** $\boldsymbol{f(X^{best}) = f_{last}},\ \boldsymbol{X^e = X^{best}}$

$c\ Flip: randomly\ generate\ an\ n - dimentional\ vector\quad \Delta(i)$

d $Move: Move\ one\ step\ according\ to\ equation$ (1), calculate $f(X(i,j+1,k,l)$

e Swim:

$Let\ m = 0$

$While$: when $\mathrm{m} < N_s$

$Let\ m = m + 1$

if $f(X(i,j+1,k,l) < f_{last}$, let $f_{last} = f(X(i,j+1,k,l)$

$Else\ m = N_s$

f **If** $\boldsymbol{f_{last}} < \boldsymbol{f(X^{best})}$, **let** $\boldsymbol{f(X^{best}) = f_{last}}$

g If $i \neq S$ the $(i+1)$ bacterium turns to step a in step 5, If $j < N_C$, go to step 4

Step 6 $Reproduction\ operation$:

$a\ Calculate\ the\ health\ of\ each\ bacterium\ according\ to\ eqaution\ (3)$

b Sort the bacteria in descending order according to the degree of health

$c\ The\ first\ half\ of\ healthier\ bacteria\ split\ into\ two\ identical\ sub - bacteria,\quad and\ the\ other\ half\ is\ eliminated$

d If $k < N_{re}$, go to step 3

Step 7 *Elimination-dispersal operation:*

Each bacterium $i = 1,2,..S$ *migrate to a new place*

$If\ l < N_{ed}, go\ to\ step\ 2$

Step 8 $\boldsymbol{Return\ the\ optimal\ solution\ (X^{best})}$

Image Registration Process and Similarity Metrics

Image registration problem requires to find the spatial transformation that maximize similarity measure between the reference and floating images. Let the reference and floating image as A and B. The image registration can be defined as

$$P^* = \arg\max \mathrm{O}(A, P_\alpha(B)) \tag{7}$$

Where P_α is the possible transformation (T) and O is the similarity measure that need to be maximized or minimized. P^* is the optimal transformation.

$$T = \begin{bmatrix} scos\theta & -ssin\theta & t_x \\ ssin\theta & scos\theta & t_y \\ 0 & 0 & 1 \end{bmatrix}\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \tag{8}$$

In this research, a rigid image registration is consider and the transformation equation used in transforming the images is shown in equation (8) (Tuba et al., 2018)

In order to find the optimum transformation parameters, the similarity metric need to be the defined for the image registration. in this research RMSE applied as a measure of error in the overall registration process. Furthermore, both MSE and RMSE are shown in equation (9) and (10).

$$MSE = \frac{1}{MN}\sum_{n=0}^{M}\sum_{m}^{N}[\hat{g}(n,m) - g(n,m)]^2 \tag{9}$$

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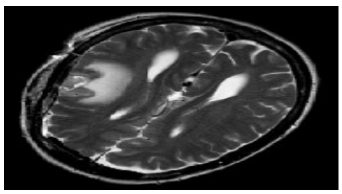
$$RMSE(\theta) = \sqrt{MSE(\theta)} \quad (10)$$

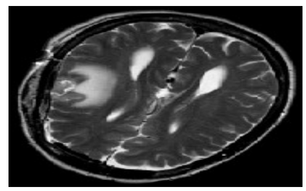
Where $\hat{g}(n, m)$ and $g(n, m)$ are the two images (Sara et al., 2019)

Table I: BRAINIX Image Transformation Parameters

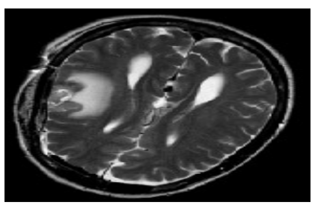
Images	Scale	θ	Cx	Cy
BRAINIX Image 1	1.2000	-10.000	20.000	20.000
BRAINIX Image 2	1.2000	9.000	-7.000	-1.000
BRAINIX Image 3	1.2000	4.000	6.000	10.000
BRAINIX Image 4	1.2000	9.000	-9.000	7.000



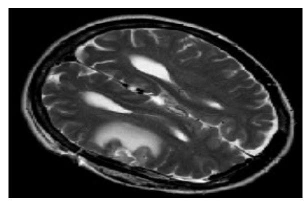
BRAINIX Image 1



BRAINIX Image 2



BRAINIX Image 3



BRAINIX Image 4

Figure 1: Brainix Image Transformations

Table II: WRIX Image Transformation Parameters

Images	**Scale**	$\boldsymbol{\theta}$	$\boldsymbol{Cx}$	$\boldsymbol{Cy}$
WRIX Image 1	1.2000	-10.0000	20.0000	20.000
WRIX Image 2	1.2000	-6.0000	-2.0000	4.0000
WRIX Image 3	1.2000	-4.0000	5.0000	-9.0000
WRIX Image 4	1.2000	7.0000	-9.0000	-8.0000

Applying the transformation in Table I and Table II, the transformation images in Figure 1 and Figure 2 are obtained according to equation (8)

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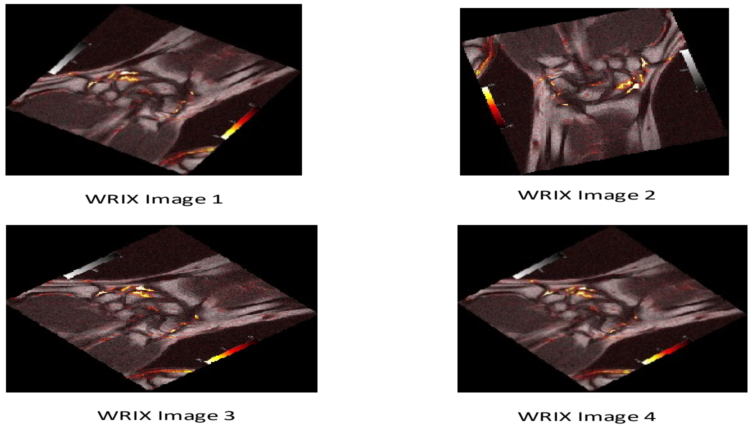

Figure 2: WRIX Image Transformations

The optimizer is an important stage in IR, it is in charge of selecting the transformation in the transformation model that has the highest similarity metric. Each optimizer has a unique search strategy, which also depends on the algorithm's structure.

RESULTS AND DISCUSSION

The performance of EOBFOA was compared with that of BFO, Opposition Bacterial Foraging Optimization (OBFO), Biogeography-Based Optimization (BBO) and Artificial Bee Colony (ABC) algorithms. The Table III indicate the results for BRAINIX Image 1. The EOBFOA obtained the least RMSE value of 0.1999 with the best translation parameter value of Cx and Cy at 4.5000 and 12.0000. The rotation angle parameter θ and Scale were obtained at 1.7000 and 1.6000 respectively. The OBFOA show the next level of accuracy with the RMSE of 0.2959 while BFO, ABC and BBO follow next ascending order.

Table III: Image Registration Results for BRAINIX Image 1

ALGORITHMS	Cx	Cy	θ	$Scale$	$RMSE$
BFO	8.9000	11.0000	-5.7000	0.9300	0.3870
OBFO	9.6000	-15.000	4.1000	1.3000	0.2959
EOBFO	**4.5000**	**12.0000**	**1.7000**	**1.6000**	**0.1999**
BBO	9.9617	-14.5411	-9.6164	1.4288	0.5308
ABC	1.4521	-6.6541	-4.0305	1.8865	0.5265

The results in Table IV represent different optimum transformation parameters for BRAINIX Image 2. The EOBFOA obtained the best $RMSE$ value of 0.2009 with the best translation parameter value of Cx and Cy at 10.0000 and -1.7000. The rotation angle parameter θ and $Scale$ were obtained at -8.3000 and 0.9800. The BBO have the next level of good accuracy with the $RMSE$ of 0.6908. The OBFO, ABC and BFO follow next in terms of accuracy

Table IV: Image Registration Results for BRAINIX Image 2

ALGORITHMS	Cx	Cy	θ	$Scale$	$RMSE$
BFO	11.0000	-10.0000	8.4000	1.4000	0.7673
OBFO	12.0000	14.0000	6.3000	0.8200	0.6988
EOBFO	**10.0000**	**-1.7000**	**-8.3000**	**0.9800**	**0.2009**
BBO	9.9617	-14.5411	-9.6164	1.4288	0.6908
ABC	-9.1484	5.8576	-3.9128	1.1866	0.7581

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The image registration results of BRAINIX Image 3 are shown in Table V. The EOBFOA obtained the best $RMSE$ value of 0.1151 with the best translation parameter value of Cx and Cy at 5.0000 and 4.0000. The rotation angle parameter θ and $Scale$ were obtained at 1.9000 and 1.4000. The OBFO have the next level of good accuracy with the $RMSE$ of 0.2059. The BFO, ABC and BFO follow next in terms of accuracy.

Table V: Image Registration Results for BRAINIX Image 3

ALGORITHMS	Cx	Cy	θ	$Scale$	$RMSE$
BFO	-18.0000	7.0000	0.7500	0.7900	0.50177
OBFO	18.0000	-11.0000	8.0000	1.1000	0.2059
EOBFO	**5.0000**	**4.0000**	**1.9000**	**1.4000**	**0.1151**
BBO	18.5950	8.1620	2.8808	1.9485	0.5184
ABC	8.8566	8.5678	1.8250	1.8794	0.5102

The image registration results of BRAINIX Image 4 are shown in Table VI. The EOBFOA obtained the best $RMSE$ value of 0.3244 with the best translation parameter value of Cx and Cy at -1.0000 and 2.7000. The rotation angle parameter θ and $Scale$ were obtained at -2.9000 and 1.4000. The OBFO have the next level of good accuracy with the $RMSE$ of 0.5334. The BBO, BFO and ABC follow next in terms of accuracy.

Table VI: Image Registration Results for BRAINIX Image 4

ALGORITHMS	Cx	Cy	θ	$Scale$	$RMSE$
BFO	0.3400	11.0000	-6.8000	0.4900	0.6146
OBFO	-16.000	-3.600	-6.300	0.6600	0.5334
EOBFO	**-1.0000**	**2.7000**	**-2.9000**	**1.4000**	**0.3244**
BBO	-14.9205	16.5350	8.1158	1.7220	0.5110
ABC	5.8512	-6.4320	1.0613	1.3478	0.7449

The WRIX image registration results of WRIX Image 1 are shown in Table VII. The EOBFOA obtained the best $RMSE$ value of 0.0164 with the best translation parameter value of Cx and Cy at -1.0000 and 6.0000. The rotation angle parameter θ and $Scale$ were obtained at 5.3000 and 1.3000. The OBFO have the next level of good accuracy with the $RMSE$ of 0.0267. The BFO, ABC and BBO follow next in terms of accuracy.

Table VII: Image Registration Results for WRIX Image 1

ALGORITHMS	Cx	Cy	θ	$Scale$	$RMSE$
BFO	0.2800	19.0000	-4.8000	0.9900	0.0487
OBFO	-15.000	17.000	8.1000	1.3000	0.0267
EOBFO	**-1.0000**	**6.0000**	**5.3000**	**1.3000**	**0.0164**
BBO	-9.0750	0.8444	5.0578	1.6640	0.1275
ABC	-5.2595	12.4574	4.4717	1.6998	0.1826

The WRIX image registration results of WRIX Image 2 are shown in Table VIII. The EOBFOA obtained the best $RMSE$ value of 0.1011 with the best translation parameter value of Cx and Cy at 2.5000 and -9.0000. The rotation angle parameter θ and $Scale$ were obtained at 2.5000 and 1.4000. The OBFO have the next level of good accuracy with the $RMSE$ of 0.1012. The BBO, BFO and ABC which follow next in terms of accuracy.

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Table VIII: Image Registration Results for WRIX Image 2

ALGORITHMS	Cx	Cy	θ	$Scale$	$RMSE$
BFO	11.0000	-18.0000	9.1000	0.7500	0.5257
OBFO	15.000	8.9000	3.7000	0.8100	0.1012
EOBFO	**2.5000**	**-9.0000**	**2.5000**	**1.4000**	**0.1010**
BBO	7.9356	-10.4699	4.3083	1.9608	0.4639
ABC	-2.4662	-6.8702	1.3064	1.8577	0.5169

The WRIX image registration results of WRIX Image 3 are shown in Table IX. The EOBFOA obtained the best $RMSE$ value of 0.0143 with the best translation parameter value of Cx and Cy at -7.0000 and 6.2000. The rotation angle parameter θ and $Scale$ were obtained at 7.7000 and 0.6500. The OBFO have the next level of good accuracy with the $RMSE$ of 0.0165. The BFO, ABC and BBO follow next in terms of accuracy.

Table IX: Image Registration Results for WRIX Image 3

ALGORITHMS	Cx	Cy	θ	$Scale$	$RMSE$
BFO	6.9000	4.5000	3.2000	1.0000	0.1181
OBFO	20.000	-17.0000	6.0000	0.5500	0.0165
EOBFO	**-7.0000**	**6.2000**	**7.7000**	**0.6500**	**0.0143**
BBO	-12.0774	7.5750	-2.9561	1.6621	0.2905
ABC	-11.6772	8.2784	-0.1222	1.7739	0.3417

The WRIX image registration results for WRIX Image 4 are shown in Table X. The EOBFOA obtained the best $RMSE$ value of 0.1112 with the best translation parameter value of Cx and Cy at -2.100 and 2.8000. The rotation angle parameter θ and $Scale$ were obtained at -5.3000 and 1.3000. The BBO have the next level of good accuracy with the $RMSE$ of 0.2423. The OBFO, ABC and BFO follow next in terms of accuracy.

Table X: Image Registration Results for WRIX Image 4

ALGORITHMS	Cx	Cy	θ	$Scale$	$RMSE$
BFO	19.0000	-18.0000	8.4000	1.2000	0.4145
OBFO	10.0000	12.000	0.6500	0.9000	0.3110
EOBFO	**-2.1000**	**2.8000**	**-5.3000**	**1.3000**	**0.1112**
BBO	-3.2099	7.7453	-3.8164	1.7155	0.2423
ABC	2.7017	-9.7972	6.9799	1.9976	0.3131

CONCLUSION

In this research, EOBFOA was applied to medical image registration using RMSE as a similarity metrics. The proposed EOBFOA was tested on two different images (BRAINIX and WRIX) with different transformation and the obtained results were compared with other nature inspired optimization algorithms. The EOBFOA obtained the best transformation parameters for the unimodal medical image registration. The algorithm can also be extended to multimodal image registration, by considering other similarity metrics and image preprocessing techniques.

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