A Comparative Study of Bio-inspired Algorithms for Medical Image Registration

D. R. Sarvamangala and Raghavendra V. Kulkarni

Abstract The challenge of determining optimal transformation parameters for image registration has been treated traditionally as a multidimensional optimization problem. Non-rigid registration of medical images has been approached in this article using the particle swarm optimization algorithm, dragonfly algorithm, and the artificial bee colony algorithm. Brief introductions to these algorithms have been presented. Results of MATLAB simulations of medical image registration approached through these algorithms have been analyzed. The simulation shows that the dragonfly algorithm results in higher quality image registration, but takes longer to converge. The trade-off issue between the quality of registration and the computing time has been brought forward. This has a strong impact on the choice of the most suitable algorithm for medical applications, such as monitoring of tumor progression.

Keywords Artificial bee colony algorithm · Dragonfly algorithm
Medical image registration · Particle swarm optimization algorithm · Swarm intelligence

1 Introduction

The objective of image registration is to align structures or regions accurately across multiple, related images acquired under different times, or at different conditions, or using different modalities [1]. This important challenge in medical image processing is an active area of research. Image registration has a multitude of applications in medical image processing. Image registration is essential for image-guided surgery [2, 3], image-guided intervention [4], radiotherapy planning, cardiac perfusion [5],

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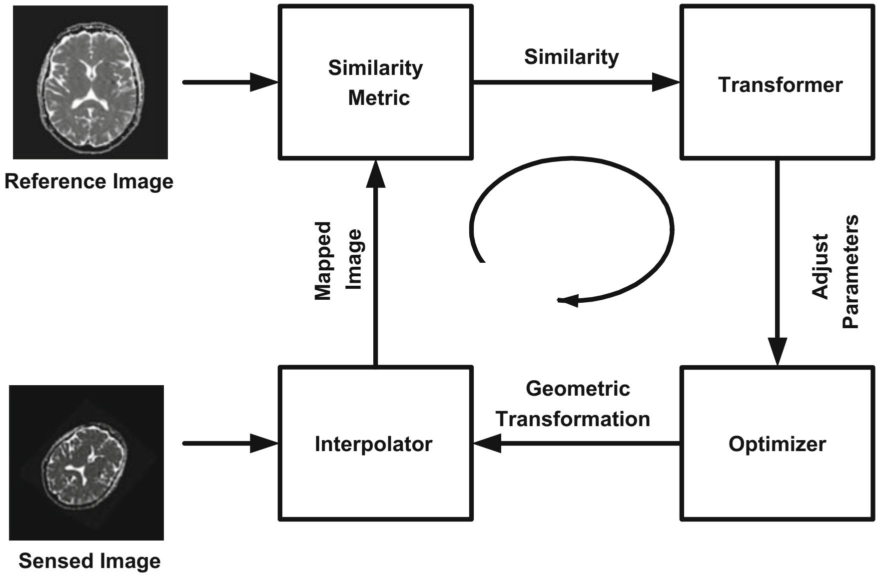


Fig. 1 The process of image registration

and monitoring of disease progression. The analysis of efficiency of treatments, such as radiotherapy and chemotherapy, requires the registration of pre-treatment and post-treatment images taken from scans. In addition, structural and functional information obtained from different imaging modalities needs to be combined for efficient determination of abnormalities which requires accurate registration. Medical image registration may involve any number of related images.

This article focuses on medical image registration using bio-inspired algorithms. In image registration, the first medical image is termed as reference image and the second as the sensed image. The procedure involves transforming the sensed image using the parameters obtained by the optimizer and calculating the similarity between the reference image and sensed image. This process is repeated until the two images are perfectly aligned. This process has been illustrated in Fig. 1.

1.1 Image Registration

Image registration is used to determine the transformation between the images. The images are either two- or three-dimensional; therefore, the transformation can be from 2-D to 2-D, from 2-D to 3-D, or from 3-D to 3-D. Intensity-based methods are widely used for registering images having same or different number of dimensions, rigid or non-rigid transformations and deformable transformations, same modality or different modality images. The reference image I_1 is fixed and does not undergo transformation, whereas the sensed image I_2 undergoes series of transformations denoted by T until it matches with the reference image. The transformed image is $I_2' = T(I_2)$. The objective of image registration is to determine the transformation T that results in maximum $I_1 \cap I_2'$. Image registration involves four major aspects: similarity metric, transformation, optimization, and interpolation.

1.1.1 Similarity Metric

The similarity metrics include the sum of squared intensity difference, the correlation coefficient, the mutual information (MI), the normalized MI (NMI), and the regional MI (RMI) [6]. MI is the measure of dependence between images and is a powerful metric to determine the similarity between multimodal images. MI is maximum for perfectly matched images. MI M is calculated using (1), where $H(I)$ is the entropy of an image I, and $H(X, Y)$ is the joint entropy of the two images X and Y.

$$M(X, Y) = H(X) + H(Y) - H(X, Y) \tag{1}$$

The NMI N is also a very powerful similarity metric for multimodal image registration. When the images are perfectly matched, the value of $N = 1$. The NMI is determined using (2).

$$N(X, Y) = \frac{H(X) + H(Y)}{H(X, Y)} \tag{2}$$

MI and NMI are the most preferred similarity metrics for intensity-based multimodal image registration, and the other metrics are typically used for monomodal image registration.

1.1.2 Transformation

A transformation function T is used to estimate the geometric relationship between the sensed and the referenced images. The estimate is then used to transform the sensed image. Transformation can be broadly classified as

Rigid transformation: Rigid transformation involves translation and rotation of the image. This is determined using (3) and (4).

$$X = x \cos\theta - y \sin\theta + a \tag{3}$$

$$Y = x \sin\theta + y \cos\theta + b \tag{4}$$

Here, a and b denote translations in x and y dimension, and θ is angle of rotation. X and Y are the transformation parameters.

Non-rigid Transformations: Non-rigid transformations involve translation, rotation, and scaling. Non-rigid transformation is determined using (5) and (6), Here, s denotes the scaling factor.

$$X = xs\cos\theta - ys\sin\theta + a \tag{5}$$

$$Y = xs\sin\theta + ys\cos\theta + b \tag{6}$$

1.1.3 Optimization

Medical image registration involves finding the right transformation parameters from a huge set. Since the set is very huge, process of optimization is essential. An optimization algorithm takes a series of intelligent guesses of the transformation parameters, applies them on the sensed image, and uses the similarity metric as the optimization objective function. This metric denotes the degree of accuracy of image registration. Image registration is performed by applying the guessed transformation parameters to the sensed image and determining the objective function on the resultant image and the reference image. The registration process continues by either guessing or obtaining new parameters and recalculating the objective function. This process is repeated until the desired objective function value is reached. An optimization algorithm updates the transformation parameters until the similarity metric between two input images reaches maximum. There are multiple optimization algorithms available in the literature. The traditional optimization algorithms include gradient descent, quasi-Newton, downhill simplex, and simulated annealing and take huge computational time to determine the optimization parameters. In addition, there are many bio-inspired heuristic algorithms, which take comparatively lesser time and less computational resources to determine the optimization parameters, and these include genetic algorithm (GA), particle swarm optimization (PSO) [7], artificial bee colony (ABC) algorithm [8], dragonfly algorithm (DA) [9], and bacterial foraging algorithm (BFA). Many hybrids of these bio-inspired algorithms, such as PSO+GA, PSO+BFA, PSO+neural network (NN), GA+NN, and ABC+NN, have been developed to achieve faster convergence and to minimize the computation time. They are popular in medical image processing as well.

To the best of authors' understanding, there is no comparative performance analysis of modern bio-inspired algorithms applied to non-rigid image registration, and also very few researchers are applying bio-inspired algorithms for medical image registration. Authors aim to bridge this gap by performing a comparative analysis of the performances of three efficient bio-inspired algorithms, namely ABC, DA, and PSO, in non-rigid medical image registration. It is hoped that it benefits researchers and doctors in deciding the best-suiting algorithm according to patients' requirements. The primary contributions of the article are as follows:

- Medical image registration has been recaptured as a continuous optimization problem.
- Bio-inspired algorithms, such as ABC, DA, and PSO, have been used as the tools to approach non-rigid medical image registration.
- Results of ABC-, DA- and PSO-based medical image registration have been presented.
- A comparative investigation of these algorithm has been presented in terms of accurateness and computing time for implementation of image registration.
- A trade-off issue between the quality of registration and computing time has been brought to fore which helps doctors in choosing an appropriate approach.

The remainder of this article has been structured as follows: A survey of literature on medical image registration using bio-inspired techniques has been presented in Sect. 2. Bio-inspired algorithms, such as ABC, DA, and PSO, have been introduced in Sect. 3. Implementation of medical image registration and MATLAB-based numerical simulations using ABC, DA, and PSO have been explained in Sect. 4. Simulation results are presented and discussed in Sect. 5. Finally, conclusions and suggestions for future extension of this research have been presented in Sect. 6.

2 Related Work

Image registration has been tackled using multiple approaches. Common among them is the information theoretic approach MI proposed in [18]. It has been proved as the best deterministic method [6]. When two images are properly aligned, their MI is maximum. The MI approach is robust against noise, sharper peaks at the more correct registration values than other correlation metrics requirement in accurate registration.

Image registration is considered as an ill-posed optimization problem and has been solved using various optimization methods, such as gradient descent, conjugate gradient, quasi-Newton, Gauss-Newton, stochastic gradient descent, Levenberg–Marquardt algorithm, graph-based methods, belief programming, linear programming, and evolutionary methods [10]. Evolutionary computation and other heuristic optimization approaches are more sturdy than the commonly used gradient-based approaches, as they are not dependent on initial solution. In addition, these approaches give specific plans to escape from local minima or maxima. These approaches have been widely used in different kinds of optimization tasks in image registration [11]. Image registration is a high-dimensional problem, computationally very intense, and involves a lot of local minima. Traditional optimization methods are likely to get trapped in local minima. Therefore, researchers have proposed metaheuristic methods to achieve good results [12]. According to a comparative study of evolutionary algorithms for image registration by [10], the best performance has been delivered by a PSO implementation. Multimodal image registration using PSO as optimization technique and NMI as similarity metric has been implemented by [13]. He illustrates the substantial potential of PSO in solving image registration. Also, PSO has proven itself as an efficient optimization algorithm in several areas [14]. The ABC algorithm has been used to solve various constrained, unconstrained, single, and multiple objective optimization problems [8, 15–17]. ABC's performance has been proved to be very efficient in other areas of research [15]. DA is the recent algorithm to join the family of bio-inspired algorithms. It has been used for multilevel segmentation and power system applications and to enhance RFID network lifetime, solar thermal plant efficiency [19–21], etc.

3 Bio-inspired Algorithms for Medical Image Registration

Nature, an affluent source of novel ideas and techniques, inspires scientists and researchers to solve many problems. The fame of nature-inspired algorithm has been attributed to their efficiency, accurate results, simple and humble computation. Three biologically inspired algorithms, namely ABC, DA, and PSO, are explained in the following subsections.

3.1 The ABC Algorithm

The ABC algorithm is an optimization algorithm which draws inspiration from the foraging behavior of natural honeybees [17, 22]. The algorithm involves three different kinds of bees, namely onlooker bees, employed bees, and scout bees. The employed bees perform exploitation of food sources and load the nectar of the source to the hive. The employed bees dance to communicate information about the food source that is being exploited currently. The number of employed bees is equal to the of number food sources. The onlooker bees look at the dance of the employed bees and, based on the dance, find out the amount of nectar in the food source. The scout bees are responsible for the exploration of newer food sources. In the process of exploitation, some food sources might become empty, and the bees which are employed and exploiting these food sources become scouts. The algorithm considers each food source position as a solution to an optimization problem and the nectar amount as the fitness of the solution. The exploration for the food is done by the scout bees and the exploitation by the employed bees. ABC has been applied to solve multiple optimization problems, and a survey on its applications in image, signal, and video processing has been presented in [12, 15].

3.2 The Dragonfly Algorithm

DA draws inspiration from dragonflies [9]. Dragonflies have a unique swarming behavior of swarming only during hunting and migration. Swarming during hunting is called static swarming and that during migration is referred to as dynamic swarming. In case of static swarming, dragonflies create small groups and fly around back and forth over small regions to hunt their preys. Local movements and abrupt changes in the flying path are the main characteristics of a static swarm. In case of dynamic swarming, a huge number of dragonflies make the swarm for migrating in a particular direction over long distances. Static swarm induces exploration behavior, and dynamic swarming induces exploitation behavior. DA is still considered an infant in the bandwagon of swarm algorithms and hence has only few applications in the area of thermal power and photovoltaic systems.

Medical image registration is treated as an optimization problem, and the parameters of optimization are the transformation parameters, namely translation along x and y axes, rotation, and scaling along x and y axes. Thus, the dimensionality of the problem equals five. These parameters are obtained using ABC, DA, and PSO algorithms, and the parameters thus obtained are checked for efficiency using the objective function NMI using (2). Implementations of image registration approached using ABC, DA, and PSO algorithms are described below.

3.3 The PSO Algorithm

PSO is a population-based algorithm [7]. It is inspired by the social behavior of bird flocking and fish schooling. It consists of a swarm of multiple n-dimensional candidate solutions called particles (n is the number of optimal parameters to be determined). Particles explore the search space for a global optimum. Each particle has an initial position, and it moves with some initial velocity. Each particle is evaluated through a fitness function. The fitness value of every particle becomes its personal best, and the minimum (or the maximum) of all particles becomes the global best. All particles try to move toward global best by changing their positions and velocities iteratively. This process is repeated until an acceptable global best is achieved or for a preset number of iterations. The PSO algorithm has been used to solve various optimization problems and has found to be efficient. It has been applied successfully in many engineering domains including wireless sensor networks [14], image registration [23], image segmentation [24], and power systems [25].

4 Numerical Simulation

4.1 Implementation

The ABC-based image registration algorithm, DA-based image registration algorithm, and PSO-based image registration algorithm have been presented in Algorithms 1, 2, and 3, respectively.

4.2 Numerical Simulation

The algorithms presented in this article have been simulated using MATLAB R2012a numeric simulations, on computer having an Intel Core i5 processor. Numerical values pertaining to case studies 1, 2, and 3 are presented in the following subsections:

4.2.1 Case Study 1: ABC-based Medical Image Registration

In this case study, ABC algorithm parameters are set as follows.

- Dimensions $d = 5$
- Abandonment limit $= 0.6 \times D \times P$
- Upper bound of the acceleration coefficient $a = 1$

4.2.2 Case Study 2: DA-based Medical Image Registration

In this case study, DA algorithm parameters are set as follows.

- Separation weight $s = 0.1$, alignment weight $a = 0.1$
- Cohesion weight $c = 0.7$, food factor $f = 1$
- Enemy factor $e = 1$, inertia weight $w = 0.9$

4.2.3 Case Study 3: PSO-based Medical Image Registration

In the study, parameters of PSO are initialized as follows. These are the standard-recommended parameters for the PSO algorithm.

- Dimensions $d = 5$
- Acceleration constants $c_1 = c_2 = 2.0$
- Inertia weight $w = 0.8$

The brain MRI tumorous images considered for simulation are Axial flair, Axial t1 weighted with and without contrast, and Axial t2 weighted and are courtesy of The

Algorithm 1 Pseudocode for the ABC algorithm

Initialize food sources m, Dimensions dim, iterations $i_{\max}$, abandonment limit of food source l
for $i = 1$ to m **do**
  for $j = 1$ to dim **do**
    Randomly initialize food source $s_i^j = s_{\min}^j + r(0,1) \times (s_{\max}^j - s_{\min}^j)$,
  end for
  Trial of each food source $t_i = 0$
end for
$k = 1$
while $k \leq i_{\max}$ **do**
  Compute $f(s_i)$ using (2) //Employed bees phase of ABC algorithm
  for $i = 1$ to m **do**
    for $j = 1$ to dim **do**
      Exploit novel food source $z_i = s_{ij} + \phi_{ij}(s_{ij} - s_{kj})$
    end for
    Compute novel food fitness value $f(z_i)$ using (2)
    if $f(z_i) < f(s_i)$ **then**
      $s_i = z_i$, $t_i = 0$ //Make the trial t of the new food source as zero
    else
      $t_i = t_i + 1$
    end if
  end for
  Determine the probability for onlooker bees $P_i = \frac{F_i}{\sum_{j=1}^{n} F_i}$
  $t = 0$, $i = 1$ //Onlooker bees phase of ABC algorithm
  repeat
    $r \sim (0, 1)$
    if $r < P_i$ **then**
      $t = t + 1$
      for $j = 1$ to D **do**
        Exploit novel food source $z_i = s_{ij} + \phi_{ij}(s_{ij} - s_{kj})$
      end for
      if $f(s_i) > f(z_i)$ **then**
        $s_i = z_i$, $t_i = 0$
      else
        $t_i = t_i + 1$
      end if
    end if
    $i = i + 1\ mod(n + 1)$
  until $t = n$
  for $i = 1$ to n **do**
    if $t_i \geq l$ **then**
      $s_i = s_{\min}^j + r(0,1) \times (s_{\max}^j - s_{\min}^j)$, $t_i = 0$
    end if
  end for
  $k = k + 1$
end while

Algorithm 2 Pseudocode for the DA

1: Initialize alignment weight a, cohesion weight c, food factor f, enemy factor e, inertia weight w Dimensions dim, Separation weight s
2: Randomly Initialize population of n dragonflies D_i
3: Initialize n step vectors δD_i
4: **while do**
5: Determine the fitness values of all dragonflies
6: Update enemy and food source
7: Update w, s, a, c, f, and e
8: For the current dragonfly D, determine S, A, C, F, and E using
Separation $Si = -\sigma_{j=1}^{N} D - D_j$
Alignment $A_i = \frac{\sigma_{j=1}^{N} V_j}{N}$, where V_j is the velocity
Cohesion $C_i = \frac{\sigma_{j=1}^{N} D_j}{N} - D$
Food factor$F_i = D^+ - D$, where D^+ is the food source of the current individual
Enemy factor $E_i = D^- - D$, where D^- is the position of the enemy
9: // Update neighbouring radius
10: **if** a dragonfly has at least one neighbouring dragonfly **then**
11: Update velocity vector using
$\delta D_{i+1} = (sS_i + aA_i + cC_i + fF_i + eE_i) + w\delta D_i$
12: Update position vector using
$D_{i+1} = D_i + \delta D_{i+1}$
13: **else**
14: Update position vector using
$D_{i+1} = D_i + \delta D_{i+1}$
15: **end if**
16: **end while**

National Library of Medicine, MedPix [26]. These tumorous images of Fig. 2 are input to the bio-inspired algorithms for determining the transformation parameters. The obtained transformation parameters are used to register the images. Results of MATLAB simulation of registering flair image with T1-weighted image using ABC, DA, and PSO are shown in Fig. 3. The results of MATLAB simulation of registering a flair image with a T2-weighted image using ABC, DA, and PSO are shown in Fig. 4. The results of MATLAB simulation of registering a T1-weighted image with a T2-weighted image using ABC, DA, and PSO are shown in Fig. 5. The results of MATLAB simulation of registering a T1 non-contrast image with a T1-weighted image using ABC, DA, and PSO are shown in Fig. 6. Results of MATLAB simulation of registering a T1 non-contrast weighted image with a T2-weighted image using ABC, DA, and PSO are shown in Fig. 7. The results of MATLAB simulation of registering a T1 non-contrast image with a flair image using ABC, DA, and PSO are shown in Fig. 8.

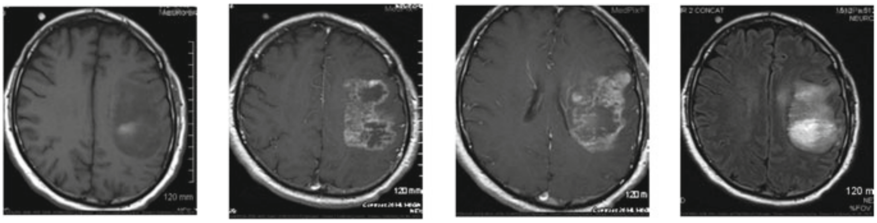
The study has been conducted with various population sizes (20, 30, 50) and iteration value of 500. Thirty trial simulations have been done. Mean of the results of 30 trials has been calculated for inference. Since the algorithms are stochastic, the solutions produced are not the same in all trials, and therefore, the results of multiple trials have been averaged.

Algorithm 3 Pseudocode for the PSO algorithm

Initialize maximum allowable iterations $r_{\max}$,target fitness function s to zero and global best value G to maximum value.
Set the values of $V_{\min}$, $V_{\max}$, $X_{\min}$, $X_{\max}$ where V denotes velocity and X denotes position
for every particle j **do**
    for every dimension d **do**
        Randomly initialize X_{jd} such that: $X_{\min} \leq X_{jd} \leq X_{\max}$
        Initialize the Personal best values P
        $P_{jd} = X_{jd}$
        Initialize v_{jd} randomly: $V_{\min} \leq v_{jd} \leq V_{\max}$
    end for
    Determine $f(X_j)$ using (2)
    if $f(X_j) < f(G)$ **then**
        for every dimension d **do**
            $G_d = X_{jd}$
        end for
    end if
end for
loop $i = 1$
while $(i \leq r_{\max})$ AND $(f(G) > s)$ **do**
    for every particle j **do**
        for every dimension d **do**
            Calculate velocity $V_{jd}(k)$
            $i_1 = c_1 r_{1jd}(k)(Xpbest_{jd}(k) - X_{jd}(k))$
            $i_2 = c_2 r_{2jd}(k)(Xgbest_{jd}(k) - X_{jd}(k))$
            $V_{jd}(k) = wV_{jd}(k-1) + i_1 + i_2$
            Restrict V_{jd} to $V_{\min} \leq v_{jd} \leq V_{\max}$
            Determine position using $X_{jd}(k)$
            $X_{jd}(k) = X_{jd}(k) + V_{jd}(k)$
            Restrict X_{jd} to $X_{\min} \leq X_{jd} \leq X_{\max}$
        end for
        Determine $f(X_j)$ using (2)
        if $f(X_j) < f(G)$ **then**
            for each dimension d **do**
                $G_d = X_{jd}$
            end for
        end if
    end for
    $i = i + 1$
end while

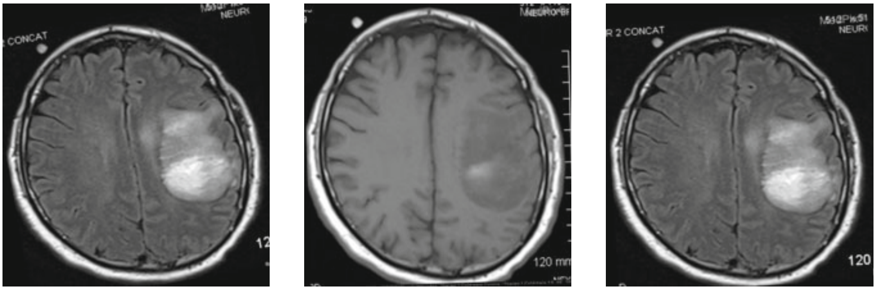
5 Results and Discussion

The brain MRI images (Flair, T1 weighted with contrast, T1 weighted without contrast, and T2 weighted) of same location having tumor shown in Fig. 2 are presented as inputs to the bio-inspired algorithms, and the transformation parameters, namely T_x, T_y, θ, S_x, and S_y, for registration have been determined using ABC, DA, and PSO algorithms. Any two of these images are the inputs to these algorithms (either Flair, T1 weighted with or without contrast, or T2 weighted). The parameters obtained



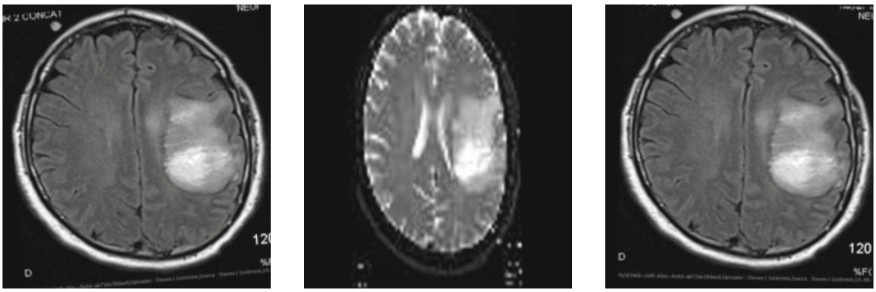
(a) T1 (b) T1non-contrast (c) T2 (d) Flair

Fig. 2 Brain axial MRI images used for registration



(a) Using ABC (b) Using DA (c) Using PSO

Fig. 3 Registration of Flair and T1-weighted images using ABC, DA, and PSO

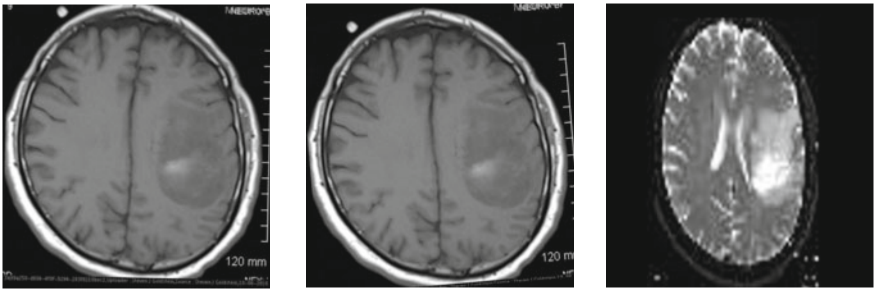


(a) Using ABC (b) Using DA (c) Using PSO

Fig. 4 Registration of Flair and T2-weighted images using ABC, DA, and PSO

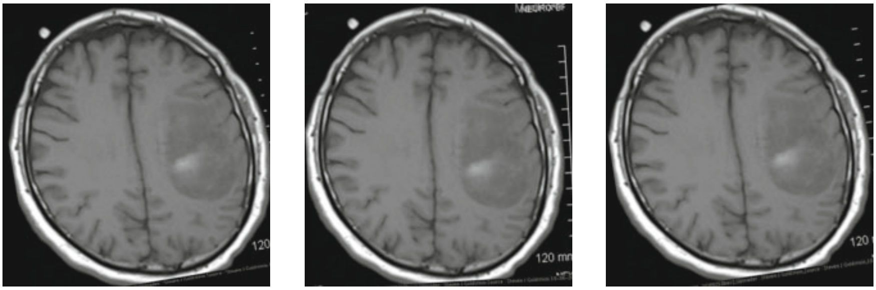
from the aforementioned algorithms are used for transformations for registration of images. It can be observed from the results presented in figures and tables that the registration using the parameters obtained from the proposed algorithms is very accurate.

The time taken for convergence and the best fitness obtained and the number of iterations taken for convergence for ABC, DA, and PSO algorithms are shown in Table 1. The results of these tables are for 10 trials with a population of 30. It can be



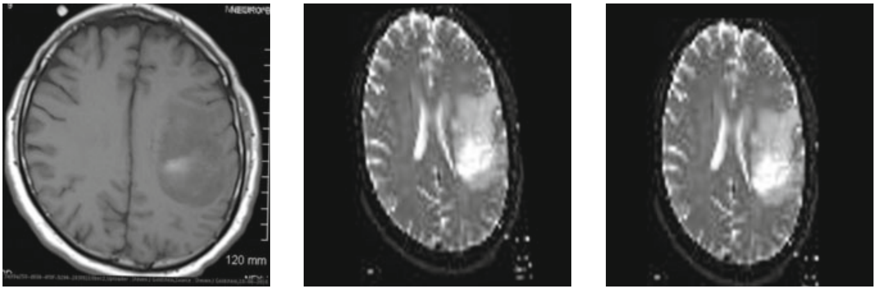
(a) Using ABC (b) Using DA (c) Using PSO

Fig. 5 Registration of T2- and T1-weighted images using ABC, PSO, and DA



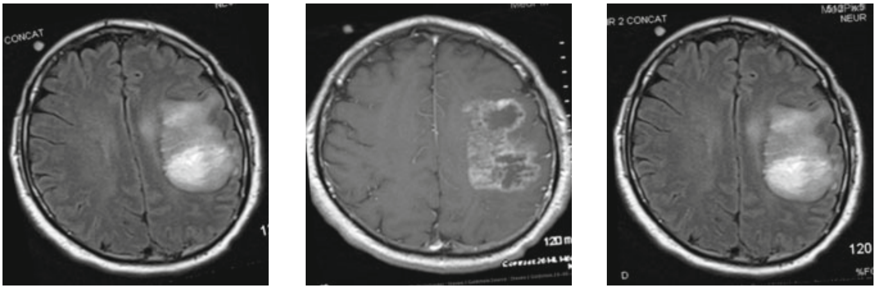
(a) Using ABC (b) Using DA (c) Using PSO

Fig. 6 Registration of T2 and T1 non-contrast weighted images using ABC, PSO, and DA



(a) Using ABC (b) Using DA (c) Using PSO

Fig. 7 Registration of T2 and T1 non-contrast weighted images using ABC, DA, and PSO



(a) Using ABC (b) Using DA (c) Using PSO

Fig. 8 Registration of flair and T1 non-contrast weighted images using ABC, DA, and PSO

observed from Table 1 the fitness value is very close to zero, and also, the time taken for convergence is in terms of seconds, rather than hours which is generally the case with traditional optimization problems.

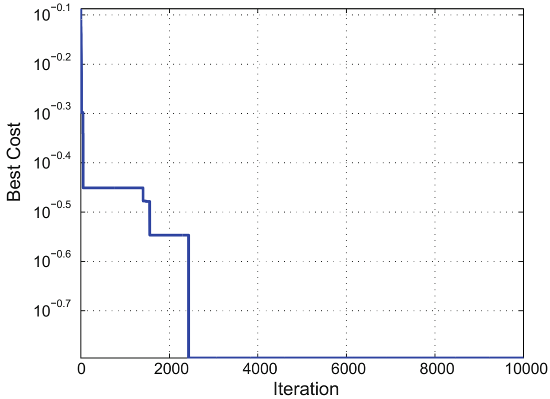
The plot of best fitness values obtained from these simulations versus iterations for population size of 20 and maximum iteration value of 10000 is shown in Fig. 9 for ABC, DA, and PSO, respectively. It can be observed that the best fitness value reaches very close to zero and also converges after 2000 iterations in all the cases. This denotes the algorithms yield good results for the determination of transformation parameters in image registration.

The mean results of 30 trial runs for varying population size of 20, 30, and 50 and maximum iterations of 500 for the ABC, DA, and PSO algorithms are given in Table 2. The table contains the mean of the best solution obtained, standard deviation of the best solution, mean convergence time, and the mean iterations of convergence. From the table, it can be observed that the obtained optimization transformation parameters are efficient, and also, the standard deviation is very close to zero, which denotes that the obtained optimization parameters using the proposed algorithms are yielding very good solutions close to the mean. The standard deviation of the algorithms becomes better with the increase in the population size.

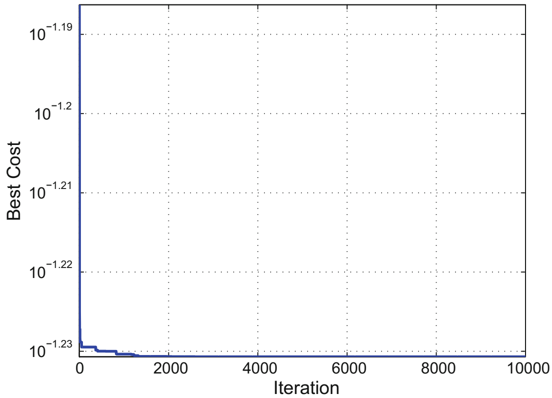
A statistical summary of 30 trials for different population sizes for the algorithms has been presented in Table 2. These tables contain the mean best solution obtained, standard deviation of the best solution, the mean convergence time, and the mean iterations of convergence. It can be observed that as the population size increases, the efficiency of all the three algorithms in terms of convergence and accuracy increases.

It can be observed from Tables 1 and 2 that DA requires more computing time when compared to ABC and PSO to obtain the optimal results. However, in terms of accuracy of the results, the DA has an upper hand over ABC and PSO algorithms. PSO takes less computing time when compared to the other two, but delivers lowest accuracy of the results. The results point out at a trade-off between accuracy and computing time. Also, as population size increases, the accuracy of all the algorithms improves, but at the cost of increased computing time.

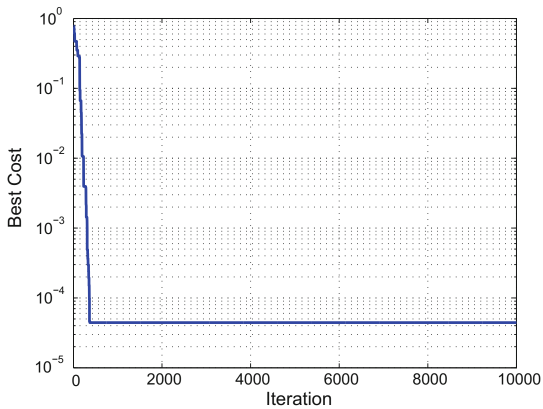
Fig. 9 The plot of the variation of NMI versus iterations



(a) Using ABC



(b) Using DA



(c) Using PSO

Table 1 Simulation results depicting obtained parameters for 10 trial runs and population size of 30 and 500 iterations

Trial	Time taken in seconds			Best fitness		
	ABC	DA	PSO	ABC	DA	PSO
1	1053.4	3671.8	390.66	0.010	6.13E-05	0.019
2	71.70	5124.3	375.25	0.007	3.72E-05	0.558
3	1080.1	3427.5	177.64	0.001	0.0039	0.342
4	650.72	5278.9	413.17	0.004	0.00043	0.505
5	559.33	5312.1	382.89	0.009	0.00045	0.544
6	749.62	2579.8	352.19	0.009	0.00011	0.349
7	469.99	2595.02	341.39	0.008	0.00093	0.562
8	1045.0	3014.5	344.78	0.030	0.00128	0.056
9	474.775	3169.3	298.93	0.008	0.0017	0.008
10	587.4	2782.0	336.47	0.009	0.00067	0.361

Table 2 Results of simulation for 1000 iterations and 30 trials

Algorithm	ABC			PSO			DA		
Population size	20	30	50	20	30	50	20	30	50
Mean fitness	0.3119	0.1404	0.0140	0.425	0.3661	0.104	**0.2147**	**0.210**	**0.1145**
Standard deviation (Fitness)	0.0575	0.0193	0.0016	0.33	0.2436	0.2088	**0.041**	**0.0525**	**0.0217**
Mean computing time (in seconds)	818	1260	2030	**403**	**871**	**1260**	2121	3342	3428

MRI images can be captured using different sequences of T1, T2, and flair. Different sequences of the same pathology give different useful information needed by the doctors, and hence, registration becomes mandatory. Accurate registration results in accurate diagnosis. The results presented in Figs. 3, 4, and 5 show that the images are accurately registered, and the registered images can be used by doctors and the radiologists in analyzing the size of the tumor during its progression and for deciding the course of treatment.

6 Conclusion and Future Work

The research reported in this article has been inspired by the success of bio-inspired, population-based search algorithms to solve the medical image registration problem. The medical image registration problem has been treated as n-dimensional continuous optimization problem. And the optimization parameters are determined using bio-inspired algorithms, namely ABC, DA, and PSO. A brief introduction to

ABC, DA, and PSO algorithm has been provided. A statistical analysis of the results obtained has been presented. The results obtained using the methods are compared.

The results show that ABC, DA, and PSO can handle the image registration successfully. However, there are some trade-off issues. While DA gives higher quality results, it suffers from longer convergence time, whereas PSO results are not as higher quality as ABC and DA, but the convergence is fast. Also, with the increase in population size, better fitness value is obtained but again at the cost of computing time in the cases. The computational complexity of DA is higher than ABC and PSO due to the greater emphasis on exploitation in the search space.

Medical image registration is a one-time exercise. Since medical image registration helps a doctor in decision making, higher quality of results is desirable. Therefore, DA is a better choice than ABC and PSO in situations in which higher precision is needed. However, a dialectical choice between these three algorithms depends on the availability of desired computational speed, computing resources, and accuracy.

This research can be extended further in multiple directions. Variants and hybrids of the bio-inspired algorithms can be developed to achieve improved quality of results and resource efficiency. These algorithms can also be applied to solve three-dimensional medical image registration, deformable image registration, and medical image fusion. Bio-inspired algorithms can also be used to address several unresolved research issues in medical image processing.

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