Effect of optimization framework on Rigid and Non-rigid Multimodal Image Registration

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Abstract-The process of transforming or aligning two images is known as image registration. In the present era, image registration is one of the most popular transformation tools in case of, for example, satellite as well as medical imaging analysis. Images captured by difference devices that can be processed under same registration model are called multimodal images. In this work, we present a multimodal image registration framework, upon which ant-colony optimization (ACO) and flower pollination algorithms (FPA), which are two meta-heuristics algorithms, are applied in order to improve the performance of a proposed rigid and non-rigid multimodal registration framework and decrease its processing time. The results of the ACO and FPA based framework were compared against particle swarm optimization and Genetic algorithm-based framework's results and seem to be promising.

Keywords- *Flower pollination algorithm, ant-colony optimization, particle swarm optimization.*

1. Introduction

In the wide domain of image processing and analysis, which includes, among others, feature extraction, pattern matching and image classification tasks, image registration has gained particular attention [1, 2]. Recent trends in in this domain suggest that image registration is a major tool in the fields of medical imaging and satellite imaging. The process of transforming one image with respect to another image is referred to as image registration. The images involved in this task can be acquired using the same or different devices [3, 4]. If the images are acquired using the same device, then the image registration task is called monomodal registration [5]. On the contrary, if the images are acquired by different devices, then the registration is called multimodal registration [6, 7].

In the recent works related to image registration, it has been observed that the several researchers have used medical videos in the registration framework. Initially, the framework breaks the input video into multiple image frames and then it proceeds to the transformation of the images [8, 9]. Such process is called monomodal registration as the video itself is acquired by the same imaging device. Medical image registration refers to registering one or more medical images with reference to another. Modality is an integral part of the image registration task. Images acquired with same device are called mono-modal images.

When the same sequence or scene is acquired with different devices, then it is called multi-modal image registration. Based on the imaging modality, the transformation matrix can change. Previously, considerably work has been focused on monomodal image registration [10]. But in this article, a comparative study of multimodal image registration is presented, and its performance optimization based on ant-colony optimization and flower pollination algorithms [11] is analyzed. Additionally, the proposed image registration framework includes both rigid and non-rigid registration algorithms [12, 13].

Rigid registration refers to the transformation of one of the images to be register based on translation, rotation, scaling or the combination of these operations. Non-rigid registration does not obey the rules of rigid registration, although they might involve the rigid transformation, i.e., translation, rotation or/and scaling. As a result, the image produced by a non-rigid registration algorithm [14-16] might have their objects warped or their shape might get changed. But, in case of rigid registration, the shape of the objects always remains intact. There have been numerous non-rigid registration algorithms [17, 18] introduced and modified over the years. In this study, the non-rigid affine registration is adopted due its similarity with rigid registration. Affine registration holds all the characteristics of rigid registration, but it also involves shearing of objects, if needed.

In the proposed framework, the objective function and scaling factor remain the same for both rigid and non-rigid affine registration [19] algorithms. In the experiments, the Roco dataset [11], which includes Computer Tomography (CT) images of lungs, was used. The images were acquired by different CT devices, which made the images multimodal.

The current work aims to optimize the performance of multi-modal registration, as it is one of the powerful tools which has a problem of producing bad result due to images being captured by different devices, resulting into dissimilarity between them. Hence, by optimizing the performance of the multimodal framework, it will be helpful for the current multimodal framework to perform better than usual, to enhance the quality of the images, as well as speed up the registration process. In this work, ROCO dataset's CT images were chosen. The fusion of the CT images can help in accurate detection and localization for any lungs related abnormality, captured by different CT devices.

This work uses different optimization algorithms for the multimodal registration framework's performance enhancement. Ant colony optimization has been proven to be one of the efficient and faster optimization techniques due its higher convergence rate. On the other hand, in our previous work, Flower Pollination algorithm has proven to be quite handful in improving the image registration process. Although we only investigated these two finest meta-heuristic algorithms [12] on monomodal images on the Demons registration framework, we chose also to use it in the proposed framework. Previously, not much has been done to optimize the performance of the multimodal [13, 14] registration. Hence, the current work aims to present an in-depth analysis of the performance optimization of multimodal registration framework, so that the framework can work better than the existing multimodal registration models. The results of the proposed framework were later compared with the results of particle swarm optimization and genetic algorithm-based based approaches.

Previous works has been discussed next. Section 3 describes the methods and algorithms used in the proposed work. The proposed work itself has been thoroughly explained in section 4. The results and their discussion have been done in section 5. Paper concludes in section 6.

2. Previous Works

Considerably amount of work has been introduced and used concerning multimodal image registration. In 2006, a multimodal image registration [5] technique was proposed by Zöllei and Wells. In this work the authors used entropy minimization to register MRI and EPI dataset pairs.

In 2011, Yi and Soatto proposed [1] the spatial-Context MI based multimodal image registration. The authors evaluated the used of mutual information (MI) between high-dimensional distributions of images and used the MI-based registration on multimodal images. In 2013, Hopp et al. used FEM models and optimization based [14] on intensity on multimodal registration, in which they used multimodal breast MRI images. They used structural similarity to optimize the framework. Arce-Santana et al. made a new approach towards multimodal [13] image registration when they used expectation-maximization (EM) to calculate displacement vectors that are used in non-rigid image registration algorithm to form the transformation matrix. In 2015, Vicente et al. discussed about a 3D Registration technique which involved multimodal images of Anatomic (MRI) and Functional (fMRI and PET) brain data [2]. They registered MRI, fMRI and PET brain images by diffusion registration to evaluate the similarity measurement among the target image and resultant image.

Multimodal 3D rigid image registration based on expectation maximization was introduced by Velazquez-Duran et al. In their work, the authors applied Expectation Maximization (EM) [4] on rigid registration integrated on a 3D Multimodal registration framework. Marcos et al. [6] discussed multimodal frameworks in geospatial correspondences, in 2016. These authors used multimodal registration on multi-sensor images in order to show land-cover update and change detection problems. In 2016, Gutiérrez-Becker et al. used multimodal Intravascular Ultrasound (IVUS) images [15] and applied deformable registration on them. In this work they used regression forest to optimize the framework and used Normalized Mutual Information to find the optimal solution. A fast predictive multimodal image registration [7] framework was proposed by Yang et al. in 2017. The authors applied Large Deformation Diffeomorphic Metric Mapping (LDDMM) registration model on two different sets of MRI brain images. Zhang et al. applied automated point set registration on multimodal retinal images in 2018. In their work, the authors used area based and feature based point set registration [8] on a set of multimodal retinal images, which were acquired using different devices. One of the recent works in the field of multimodal registration involved Hu et al. using convolutional neural networks on the framework. In this work they used deformable registration on MR and TRUS images. Blendowski et al., in 2019, proposed multimodal image registration [3] using shape encode-decoder. In this work, anatomical shape information is used for transformation matrix generation, and the proposed registration method is applied on 3D scans of whole heart. Adaptive stochastic gradient descent search implemented on non-rigid and affine [16] multimodal registration framework by Daly et al. In this work, they used RIRE database images which were multimodal.

Hence, it is clear that a significant amount of work has been done in the field of multimodal registration [17, 18] framework, but all of them lacks proper optimization of the framework and analysis of such optimization technique. In the present work, we tried to analyze and inspect the performance optimization of the multimodal [19, 20] image registration framework.

3. Image Registration frameworks

Based on the imaging modalities and the transformation involved, the image registration process can be divided into four groups:

a. **Monomodal Registration:** Monomodal registration [21, 22] refers to the registration process where the images involved are acquired by the same device. In such registration, there can be many applications, where the registration happens using images obtained from the same video. Also, monomodal registration [23] can be done, for example, on the acquired images by the same satellite for any moving object. The monomodal registration totally relies on the modality of the images rather on the acquisition device.

b. Multimodal Registration: Mutlimodal registration [16] refers to the process of registering images [24] acquired by different devices. This is one of the more complex cases of registration, as the registration framework often led to erroneous registrations due to the dissimilarity between the images in terms of resolution, size or even in terms of hue, saturation, contrast or color. If the dissimilarity is high, then it becomes almost impossible to establish a transformation matrix, which leads to registration [25, 26] process failing. In the current work though, two multimodal images were chosen carefully, based on their similarity [27] with each other, so that the images doesn't become too much different from each other, leading to erroneous registration. The case of erroneous registration is mostly found when the acquisition devices are completely different.

c. Rigid Registration: The concept of rigid registration [20] is based on rigid transformation. The rigid transformation or rather rigid registration process only involves the transformation matrix [21] based on rotation, scaling and translation. These three geometrical operators, which can be applied individually or combined, are the key behind the rigid registration. The key significance of the process is: the shape of the objects in the images will never be changed or distorted as a result of the registration process as only rotation, scaling and translation are applied during the process.

d. Non-rigid Affine registration: Non-rigid registration refers to the registration which includes transformation of images which often forces the shape of the objects in the images being changed. There are various algorithms and techniques available in case of non-rigid registration such as: Affine registration, B-Spline's registration [27, 28] and Demons registration [29, 30]. In this study, affine registration [30] was chosen to represent the non-rigid registration [31] category, due to its vast similarity with the rigid registration. Affine registration uses affine transformation that includes rotation, scaling and translation like rigid transformation, but it also includes shearing, mapping and reflection, which forces to change the shape of the objects involved in the registering images.

4. Optimization techniques

There are several optimization techniques that have been used in image registration [30]. Among them, a faster and a performer algorithm was chosen: the Ant Colony optimization algorithm.

a. Ant Colony Optimization

Ant Colony optimization [32] is a probabilistic algorithm used to solve problem statements by searching for optimal paths using graphs. The multi-agent method is used in this algorithm, which is inspired by the behaviour of real ants. The process of Ant Colony Optmization [33] has five main steps:

(1) **Initialization:** The heuristic information and pheromone information are used to initialize the parameters of the algorithm.

(2) **Solution construction:** for ant k=1 to n, the new solution is evaluated. The probabilistic rule [40] is used in this step in order to identify new components for the solution. This probabilistic rule is sub-problem of k, which is the current state's function. It also uses pheromone and heuristic function.

(3) **Solution evaluation:** for every ant acquired in step 2, the non-dominated solutions should be saved and the dominated solutions deleted.

(4) **Update of pheromone matrices:** the pheromone matrix should be updated from the extracted information of new solutions.

(5) **Termination:** The algorithm stops when the stopping criteria is met. The non-dominated solution is retrieved as an output. If it does not find the stopping condition, then it goes back to step 2.

Steps 1, 2 and 4 identify the significance and differences between the ants involved. Various kind of initialization, pheromone matrices update often leads to hybrid Ant Colony Optimization. There are various types of ant colony optimization available based on their initiation procedure, such as:

i) single-group and multiple-group;
ii) single-pheromone matrix and multi-pheromone matrix;
iii) single-heuristic matrix and multi-heuristic matrix;
i) Single-group/multi-group ACO [34], which is based on the division of the ants into single or multiple different groups. All ants in a single group ACO share the common pheromone information. The heuristic information for all ants is also the same in case of single groups. Change of pheromone information affects the solutions [34] in such cases. For multi-groups ACO, the ants are divided into separate groups. It is possible to concatenate the generated solutions in case of multi-group. The solutions of each group can be merged and then can be reassigned to the groups. Hence, it can be said that the groups are not at all unrelated and they can interact with the help of the marginal ants. The key objective of all this is to update the pheromone information.

ii) In the ant colony algorithm [33], the number of pheromone matrices refers to whether the algorithm is single-pheromone or multi-pheromone. In case of single pheromone, the ants share a single pheromone matrix and work on solutions to update that pheromone matrix. In multi-pheromone matrix, each pheromone matrix affects the generated solutions.

iii) ACO [34] also offers an option of having single heuristic matrix or multiple heuristic matrices. Multiple heuristic matrices are aggregated into a single heuristic matrix while generating the solution, in case of multi-heuristic matrix approach. In case of single heuristic, there is no such problem, as all ants share the same heuristic matrix.

For example, in the case of the travelling salesman, problem Ants [30] will use a probabilistic rule to identify the best city to visit next. The pheromone information and heuristic information determines this probabilistic rule. In fact, it is the function of the pheromone [33] and heuristic information that are applied to evaluate the probability of the next city to visit. Additionally, the roulette wheel selection can be applied to choose the next city.

There are various ways to update pheromone information. The non-dominated solutions [34] can be used to update the pheromone matrix. The optimal solution of each weight vector can be used to update the information of pheromone matrices. For every objective, there is an optimal solution, which can again be used for the updating of pheromone matrices. The process of updating pheromone information can be different, but each of the process affects the quality of the solution.

b. Flower Pollination Algorithm

The pattern of pollination of flowers inspired the concept [35] behind Flower Pollination Algorithm. The main aim of this bio-inspired algorithm is to find optimal solution for any problem statement. Pollination can be biotic or abiotic. The transfer of pollens happens using pollinators such as insects, birds or other animals, in case of biotic pollination. The abiotic pollination [38] does not involve any pollinators. Pollinations can also be of two types: Self or Cross pollination. If the flower's pollen transfer to different flower of same plant, then it is called self-pollination. Conversely, if the pollination happens with other flower [36] of other plant, then it is referred as cross pollination. As aforementioned, animals or birds or insects are often involved in the process of pollinations, acting as pollinators. These birds or insects do obey the Levy distribution while flying, making their motion containing levy flights rules. The pollinators only fly to specific flowers in search of food. The food reliability related to the definite species of flower affects the pollination, resulting in maximization of reproduction.

From the above-mentioned discussion, FPA follows the following specific rules [35]:

a) Local pollination includes Self-pollination and abiotic pollination;
b) Global pollination includes Cross-pollination and biotic;
c) If individual pollinators' stay at certain flower species or even if it changes to another species, then it is referred as flower devotion. Hence, correlation of the two flowers involved heavily affects the probability of reproduction;
d) Local- and global-pollination depends on the probability denoted by $p \in [0, 1]$. The probability relies on aspects such as wind, climate, physical proximity, etc.

Global pollination involves pollinators [36] as they help the pollens to travel to a distance. Hence, the evaluation of the pollination fittest (g^*) solution is guaranteed in global pollination. The global pollination rule is defined as:

$$A_u^{t+1} = A_u^t + B(A_u^t - g^*) \quad (1)$$

where u is the solution vector, A_u^t is the pollen [34] that refers to A_u at iteration t, the current best solution is denoted by g^*, the pollination strength, or the step size, is denoted by B, with $B > 0$ as the pollinators involved in the process do obey the Levy flights.

5. Proposed Method

The current study focused on optimizing a multimodal registration framework.

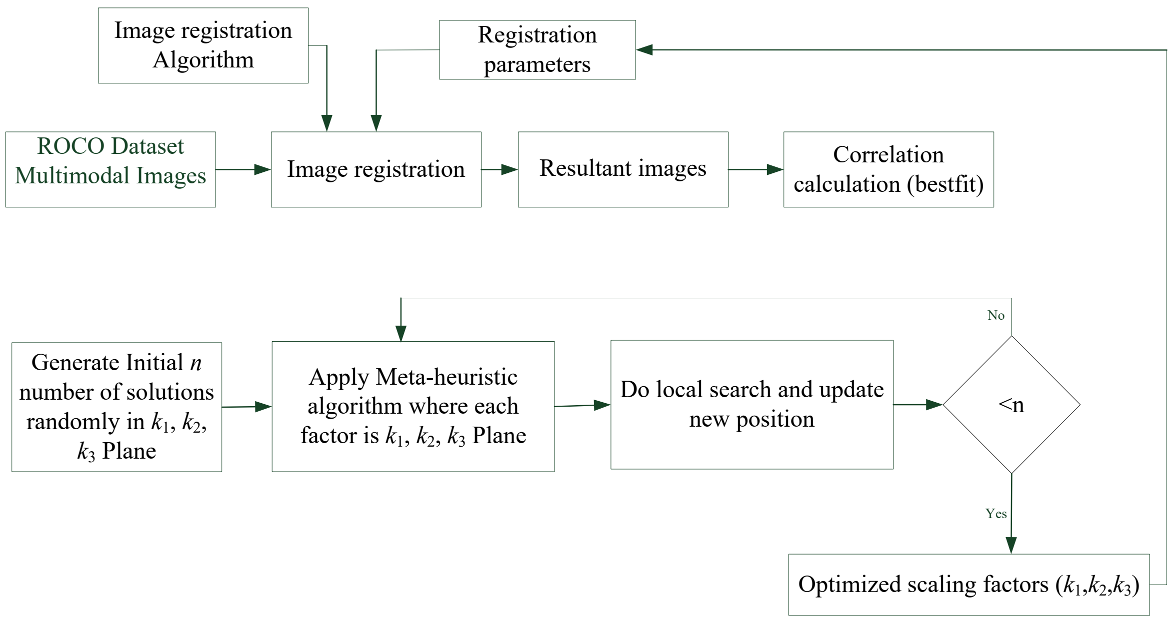


Fig. 1 Flow Chart of the optimized framework.

Fig. 1 indicates that the ROCO dataset [11] of multimodal images was used. Hence, multimodal images were selected and passed on to the framework. The registration process involved both rigid and non-rigid affine transformations. The optimization process is achieved using the meta-heuristic algorithms in the registration framework. In the current study, Flower Pollination algorithm was used and compared with other meta-heuristic algorithms such Ant Colony Optimization, Particle Swarm Optimization [37] and Genetic Algorithm [38]. Also, the Initial Radius, Epsilon and Growth Factor of Rigid and Affine transformations were used as scaling factors. The values of the scaling factors and the correlation between the reference and registered images using the default values are indicated in Table 1

Table 1: Values of the used scaling factors

	Initial Radius	Epsilon	Growth Factor	Correlation (Original vs Registered)
Rigid Registration	0.009	1.5e-4	1.01	0.8183
Affine Registration	0.009	1.5e-4	1.01	0.8206

6. Results and Discussion

a. Dataset

The dataset that has been used in the current study is the ROCO [11] dataset. The ROCO refers to Radiology Objects [11] in COntext (ROCO). This dataset contains a large amount of multimodal medical images, which has been used for image captioning generative models as well as in image classification. There is a subset of the ROCO dataset which is available at ImageCLEF 2019 [11] and has been used for concept detection task.

b. Analysis

In the current study, a Intel i3, 2.2 GHz processor-based system and MatLab R2018a were used which is an essential tool for image processing, RGB color analysis in images [39], Machine learning [40]. MatLab R2018a was used for running the image registration algorithm Flower Pollination Algorithm, Ant-Colony Optimization, Particle Swarm Optimization and Genetic Algorithm. From the ROCO dataset, multimodal computed tomography (CT) images of a pectus excavatum patient lungs were chosen for testing the current image registration framework. The performance evaluation metric that was used, was the correlation coefficient between the reference and resultant images, which was calculated as [18]:

$$corr = \frac{\sum_a \sum_b (\mathrm{K}_{ab} - \mathrm{K}^{'})(\mathrm{L}_{ab} - \mathrm{L}^{'})}{\sqrt{(\sum_a \sum_b (\mathrm{K}_{ab} - \mathrm{K}^{'})^2)(\sum_a \sum_b (L_{ab} - \mathrm{L}^{'})^2)}} \text{.............(2)}$$

Table 2 reports the found evaluation metric values and the three optimized parameters, namely k_1, k_2 and k_3 for the ant colony algorithm based affine multimodal registration framework.

Table 2: Ant-Colony algorithm based Affine multimodal registration

Iterations	k_1	k_2	k_3	Correlation	Time (sec)
5	74	72	71	0.9055	19.41
10	97	94	97	0.9045	70.59
15	99	99	99	0.9059	119.59
20	99	99	99	0.9059	172.09
25	99	99	99	0.9059	203.51
30	99	99	99	0.9059	241.47

In Fig. 2a, one can observed that after 15 iterations, the optimal best fitness value was obtained, which was equal to 0.9059. The original, reference and the resultant images are shown in this Fig. 2a.

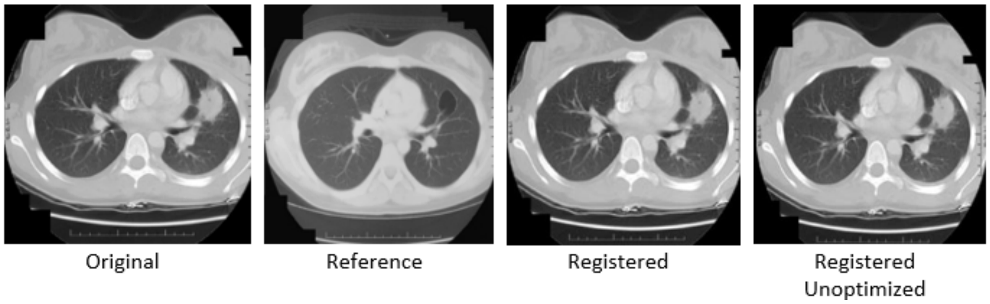


Fig. 2a Original, Reference, and Registered and Registered without optimization images using the Ant-Colony algorithm based Affine multimodal registration.

Table 3 indicates the k_1, k_2 and k_3 values for Ant-Colony algorithm based on the rigid multimodal registration. The population was kept fixed at 15, while iterations were increased by 5, from 5th to 30th generations.

Table 3: Ant Colony Optimization algorithm-based Rigid multimodal registration

Iterations	k_1	k_2	k_3	**Correlation**	**Time (sec)**
5	57	54	56	0.7596	24.19
10	97	97	97	0.9575	89.04
15	99	99	99	0.9584	127.96
20	99	99	99	0.9584	211.92
25	99	99	99	0.9584	247.13
30	99	99	99	0.9584	280.37

In this case, also after 15th iterations, the values got converged, being the best fitness value obtained equal to 0.9584. From Table 3, it can also be realized that Ant-colony [32] performed faster than the other algorithms used in the registration framework. The obtained registered image as well as the original, target or reference image and registered image with default framework are shown in Fig. 2b.

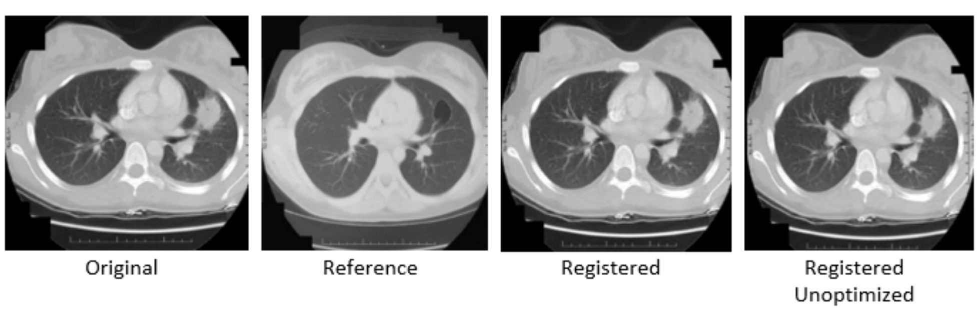


Fig. 2b Original, Reference, and Registered and Registered without optimization images using the Ant-Colony algorithm based Rigid multimodal registration

It can be observed in Table 4, k_1, k_2 and k_3 values for the Flower Pollination algorithm [35] based Affine multimodal registration framework. The iterations were varied from 5 to 30 while keeping the generation set always at 15.

Table 4: Flower Pollination algorithm based Affine multimodal registration

Iterations	k_1	k_2	k_3	Correlation	Time (sec)
5	52	61	64	0.7608	765.24
10	71	72	86	0.8780	1554.63
15	92	98	98	0.9063	2515.98
20	98	98	98	0.9184	3221.76
25	98	98	98	0.9184	4139.22
30	98	98	98	0.9184	5067.39

From Table 4, it is clearly realized that after the 20th iteration, the convergence was achieved and the best fitness value obtained was of 0.9184. As previously noted, the best fitness was the correlation value [35] between the reference and resultant images. The original, reference and registered images are shown in Fig. 2c.

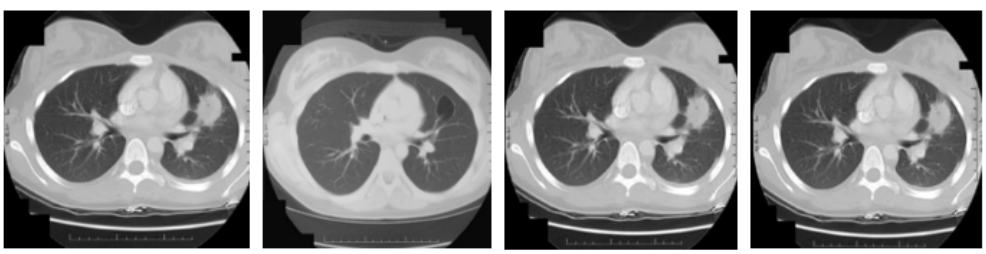


Fig. 2c Original, Reference, and Registered and Registered without optimization images using the Flower Pollination algorithm based Affine multimodal registration

To make the analysis more prominent, the same framework was also applied using the rigid registration algorithm. The obtained values can be found in Table 5.

Table 5: Results found for the Flower Pollination algorithm based Rigid multimodal registration

Iterations	k_1	k_2	k_3	Correlation	Time (sec)
5	67	65	72	0.7496	287.78
10	78	85	82	0.9564	411.38
15	98	98	98	0.9584	887.24
20	99	99	99	0.9584	1276.83
25	99	99	99	0.9584	1667.34
30	99	99	99	0.9584	1975.18

The obtained results are better than the results obtained based on affine registration using FPA [36], although they are almost identical to the ones obtained using the ant-colony optimization [31] based Rigid registration framework's optimal best fitness values. It should be noted that the current framework took longer time than the ACO based Rigid registration model in each iteration, although the convergence of the process was found earlier than the ACO based model. The ROCO dataset images and the resultant image of the current framework are shown in Fig. 2d.

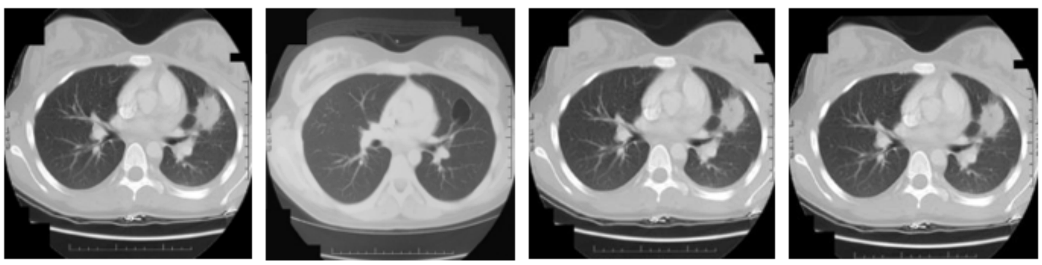
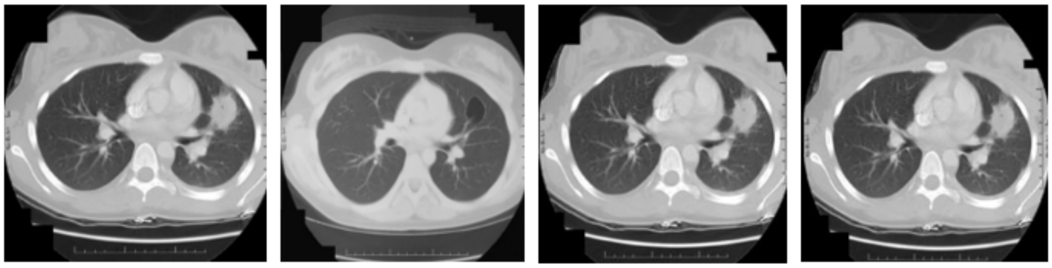


Fig. 2d Original, Reference, and Registered and Registered without optimization images using the Flower Pollination algorithm based Rigid multimodal registration

Table 5 presents the results obtained using the genetic algorithm based Affine multimodal registration. The data of this table indicates that the genetic algorithm-based framework [38] might have performed faster, but the optimized values and results were quite poor compared to the ones obtained by the other frameworks. The obtained images are shown in Fig. 2f.

Table 5: Results obtained by the Genetic algorithm based Affine multimodal registration

Iterations	k_1	k_2	k_3	**Correlation**	**Time (sec)**
5	96	94	96	0.9055	398.65
10	92	92	90	0.9277	763.51
15	96	96	95	0.9285	1213.11
20	98	98	98	0.9184	1561.68
25	98	98	98	0.9184	1985.47
30	98	98	98	0.9184	2436.54



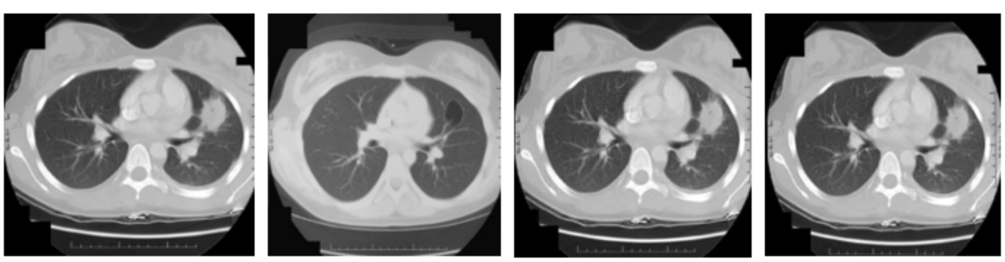
Original Reference Registered Registered Unoptimized

Fig. 2f Original, Reference, and Registered and Registered without optimization images using the Genetic Algorithm based Affine registration

Table 6 presents the results obtained using the genetic algorithm based Rigid multimodal [11] registration. These results suggest that the genetic algorithm-based rigid framework performed faster and that the results were quite better than the ones of the affine framework. Fig. 2e shows the resultant images [39] from the Genetic Algorithm based rigid registration framework.

Table 6: Results obtained by the Genetic algorithm based Rigid multimodal registration

Iterations	k_1	k_2	k_3	**Correlation**	**Time (sec)**
5	83	83	85	0.9573	393.88
10	96	96	95	0.9570	800.52
15	99	99	99	0.9584	1311.72
20	99	99	99	0.9584	1765.53
25	99	99	99	0.9584	2112.47
30	99	99	99	0.9584	2563.32



Original Reference Registered Registered Unoptimized

Fig.2e Moving, fixed and registered images using the Genetic Algorithm based Rigid registration

The same study was performed using Particle swarm optimization [37], which led to the results presented in Table 7.

Table 7: Results obtained using the Particle Swarm Optimization based Affine multimodal

Iterations	***k*₁**	***k*₂**	***k*₃**	**Correlation**	**Time (sec)**
5	65	78	81	0.8765	521.12
10	81	86	98	0.9070	952.03
15	98	98	98	0.9184	1505.93
20	98	98	98	0.9184	2122.15
25	98	98	98	0.9184	2732.71
30	98	98	98	0.9184	3411.27

The results in Table 7 let one conclude that the method was optimized after 15th iterations, but the results were not as good as the ones obtained using the Genetic Algorithm's rigid registration framework. PSO based Affine registration framework's obtained images are shown in Fig. 2h

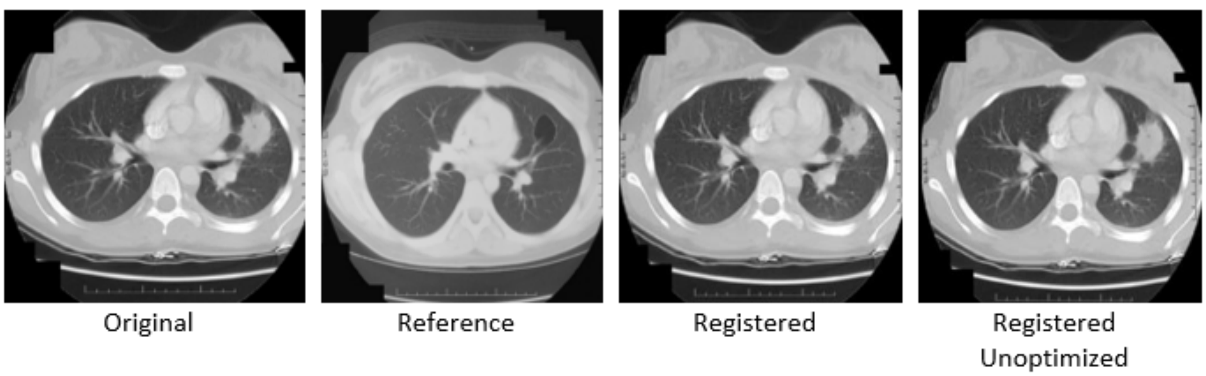


Fig. 2h Original, Reference, and Registered and Registered without optimization images using the Particle Swarm Optimization based Affine registration

The rigid registration-based framework was also applied using Particle Swarm Optimization, Table 8.

Table 8: Results obtained by the Particle Swarm Optimization based Rigid multimodal

Iterations	***k*₁**	***k*₂**	***k*₃**	**Correlation**	**Time (sec)**
5	71	49	74	0.7628	497.85
10	92	79	74	0.8780	926.88
15	99	99	99	0.8775	1428.72
20	99	99	99	0.8775	1923.87
25	99	99	99	0.8775	2671.33
30	99	99	99	0.8775	3212.73

It can be realized from Table 8 that the PSO based Rigid registration produced the worst results among the methods discussed here. The original, target and registered images obtained from PSO based Rigid registration framework are shown in Fig. 2i.

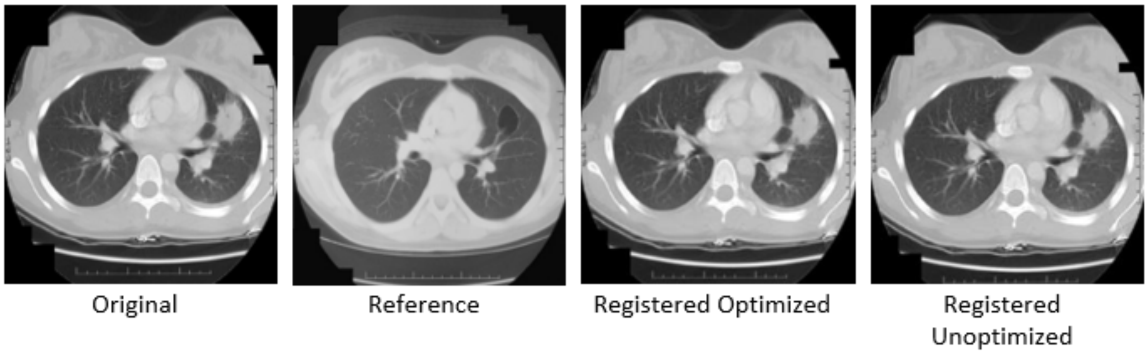


Fig. 2i. Moving, fixed and registered images using the Particle Swarm Optimization based Rigid registration

Rigid transformation seems to be faster than affine transformation due to its simplicity and less parameters involvement. Fig. 3a supports this observation taking into account different metaheuristic [39, 40] framework based Non-rigid Affine and Rigid registration.

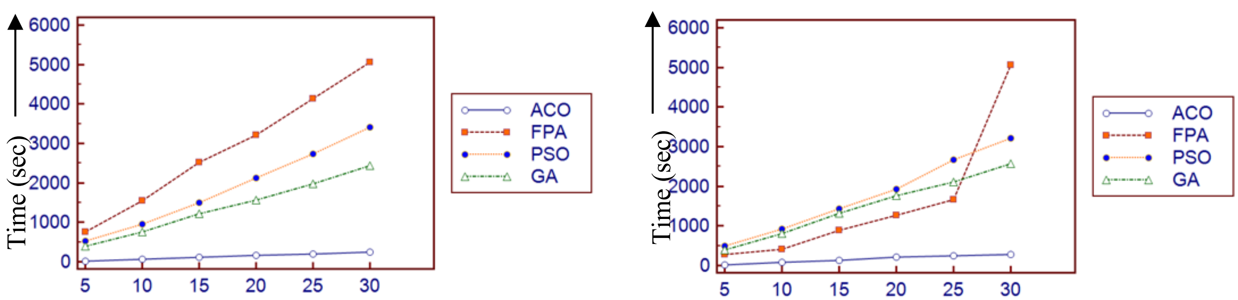


Fig.3a. Analysis of the time complexity in various metaheuristic based multimodal Non-rigid affine (Left) and Rigid (right) registrations

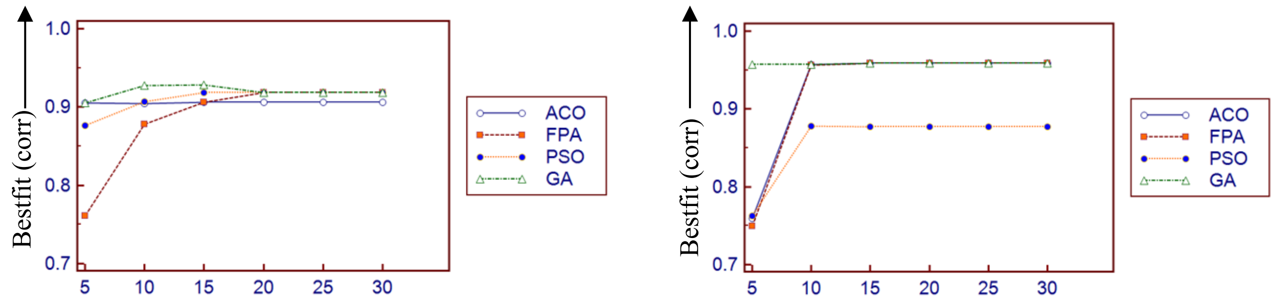


Fig.3b. Analysis of the best fitness values (correlation) in various metaheuristic based multimodal Non-rigid affine (Left) and Rigid (right) registrations

As shown in Fig. 3b, Ant-colony optimization performed clearly faster than Flower Pollination, Genetic algorithm and particle swarm optimization. Although it can be observed in Fig. 3b that in terms of performance and results, the Flower Pollination algorithm based rigid registration outperformed all other methods discussed in the current work.

c. Discussion

In the present study, the focus was on registering multimodal images obtained from the ROCO dataset [11]. The scaling factors of rigid and affine registrations [4] were optimized and the correlation between the target and resultant images [40] was considered as the fitness function. Hence, the scaling factors causing to achieve the best fitness was stored in each iteration. After the 30th iteration, it was observed that Flower Pollination Algorithm [37] was superior in terms of best fitness, which means that the resultant image produced by FPA based Image registration framework (for both Rigid and Affine registrations) was the best among other the studied optimization frameworks. Although, in terms of time complexity, it was observed that Ant-Colony Optimization [31-33] outperformed all other techniques, as it converged and did the processing of registration faster than all the other compared frameworks.

7. Conclusion

The current study was aiming to investigate the results of optimization and improving the resultant image of image registration on a multimodal dataset. It was observed that, as a result of the optimization, the image registration was improved in every aspect. Ant-Colony optimization and Flower Pollination algorithm were key highlights of the four studied meta-heuristic algorithms, but, overall, it can be realized that the default registration values were quiet behind than the results of every meta-heuristic based multimodal image registration framework. Ant-colony optimization was the fastest among all, the whereas Flower Pollination Algorithm based framework produced the highest fitness value among all studied frameworks, in case of rigid as well as non-rigid affine registrations. Affine transformation was mainly chosen because of its similarity with rigid registration, although it falls under the category of non-rigid transformation.

Future work, may include inspecting on other multimodal image registration frameworks, such as mutual information-based frameworks and the effects of optimization on the scaling factors of those registration models.

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