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Multimodal Medical Images using Rigid Iconic Registration based on Flower Pollination Algorithm and Butterfly Optimization Algorithm

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Abstract— One of the numerous challenges of modern image processing is image registration. Information from many images often emerges in slightly different forms and is highly compatible. Spatial alignment is crucial to merge essential and valuable information from several images properly. The term "registration" describes this procedure. Find a transformation that results in a model that closely resembles the reference image [1].

Mainly, this work is concerned with implementing two optimization algorithms: the Flower Pollination Algorithm (FPA) and the Butterfly Optimization Algorithm (BOA). To measure the efficacy of these methods, we compare the transformed image to the original by computing the mutual information between the two. The effectiveness of these methods was assessed using SSIM, EQM, and MI measures. Results from the experiments indicate that the BOA outperforms the FPA.

Keywords—medical image registration, Flower Pollination Algorithm, Butterfly Optimization Algorithm.

I. INTRODUCTION

Image registration holds a prominent place in many fields of research such as medical, satellite or optical imaging or essentially in any field involving registration. More specific examples supported by included logging, remote sensing (build a global picture from different micro-views), security (compare existing images to a database), robotics (object tracking), in particular medicine, integration of different modalities, planning of treatment interventions, follow-up diseases, radiotherapy [1].

The registration processes are extremely complex, diverse and adapted to the many types of sensors used. As a result, two basic techniques for registration exist: the geometric and iconic approaches and an approach that combines them. Geometric techniques are based on the extraction of geometric primitives from the image in order to estimate the best registration transformation. The iconic techniques, for their part, exploit the information conveyed by the intensity levels of the images to be readjusted. They are essentially consistent in optimizing similarity criteria based solely on intensity comparisons [2].

The application of meta-heuristic optimization algorithms in the iconic registration problem is recent, the results of this application showing remarkable improvement and optimization [3] [4]. In this context, we propose to use two novel approaches for rigid iconic registration, using two metaheuristic algorithms; the flower pollination algorithm [5] and a relatively new optimization method called "butterfly optimization algorithm" [6].

The key contributions of our paper are summarized as follows:

- calculate the best rigid transformation (Tx, Ty, θ) which allows to correctly align the two images I_{ref} and I_{cib}
- we have evaluated the effects of FPA and BOA and their influence in image registration.
- The Harvard University Medical School's Whole Brain Atlas Database is used for extensive modelling and simulations.
- Our main contribution is to compare the influence of FPA and BOA on performance of mono and multimodal medical image registration processes, using different variance and study its effects with three metrics which is "Mean Squared Error" (MSE), "Mutual Information" (MI) and "Structural Similarity Index" (SSIM).

The rest of this paper is organized as follows:

The literature on the registration process in Section 2 outlines the two algorithms, FPA and BOA, in Section 3. In Section 4, we analyze the findings of the experiments, including a discussion of the metrics and data sets employed, a summary of the results, and an analysis of the data. Conclusions and suggestions for future study are provided in Section 5.

II. IMAGE REGISTRATION PROCESS

Image registration is widely used in several areas of image processing, it is a discipline that has made significant progress in various sectors, including medical, satellite and optical imaging. Matching a series of photos to process their respective information is one of the most difficult tasks in image processing. Image registration is a technique that consists in calculating spatial transformations between images

in order to maximize the similarity criteria [7]. The registration process is shown in figure 1[8].

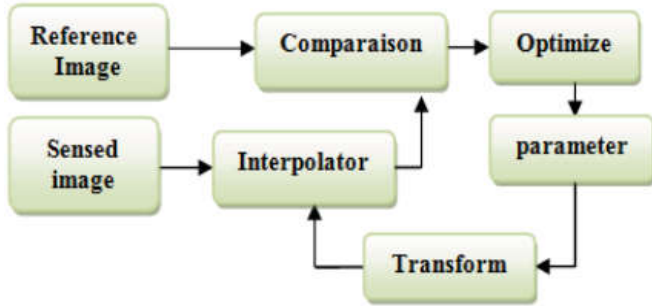


Figure 1: Block diagram of image registration process

In the field of image processing, registration is a method for creating visually identical copies of an image for the purposes of analysis or fusion. Finding the best geometric transformation to align one image (the "target") onto another (the "reference"), whether the images were taken at the same time or at separate times, is the objective of image registration. Figure 2

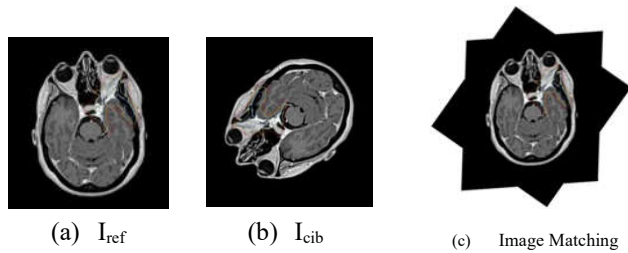


Figure 2- Example of image registration.

III. FLOWER POLLINATION ALGORITHM (FPA) AND BUTTERFLY OPTIMIZATION (BOA) BASED OPTIMISZATION ALGORITHM.

A. Methods présentation

In 2018, Arora and Singh proposed the Butterfly Optimization Algorithm (BOA), a new nature-inspired metaheuristic optimization algorithm that mimics the foraging abilities of biological butterflies and the mating behaviour of butterflies [9]. The algorithm's method and concept were first proposed at an international conference in 2015.

A.1 Biological and natural behavior

Smell is the most important sense of a butterfly because it helps butterflies find food, which is nectar. Butterflies mainly use sensory receptors which are used in smell to discover sources of nectar, and these receptors are distributed throughout the body of butterflies like antennae. And legs and palps. Chemoreceptors are nerve cells located on the surface of the butterfly's body. The butterfly uses these chemical receptors to find the optimal mating partner [10].

Butterflies emit a scent that varies in intensity as they move from place to place. The movement of search agents (butterflies) in the BOA algorithm is guided by this smell. If a

specific butterfly fails to detect the scent of another butterfly inside the search space, it will engage in exploitation (local search) by moving to a new, randomly chosen position. Some butterflies can smell the scent of the best butterfly and move towards it via a global seeking mechanism, known as crawling [10], [6], [11].

The scent is defined according to the intensity of the stimulus as follows:

$$F = cI^a$$

F: is the volume of fragrance emitted by a given butterfly.

c: is the sensory modality.

I: is the intensity of the scent stimulus emitted by the butterfly

a: is the power exponent that depends on the sensory modality with its values in the range [0, 1] where:

If a=1: means a nearby butterfly can smell the full scent. This is the case in an ideal environment, there is no absorption of perfume by the surrounding space.

If a = 0: the scent generated by a single butterfly cannot be felt by any other butterfly.

Like the pollination behaviour of flowers, the flower pollination algorithm is a metaheuristic algorithm that takes its cues from nature. By comparing its results to those of other metaheuristic algorithms [12], Yang developed FPA in 2012, demonstrating its superior performance.

A.2 Flowers

A flower is the reproductive organ of flowering plants and its biological role is to combine male pollen and female ovum to form seeds and spores. Pollination is the first step, followed by fertilization which leads to the development and distribution of seeds. Seeds are the primary means by which members of the same phylum have spread throughout the world and represent the next generation of higher-class plant reproduction.

There are two types of reproductive spores produced by flowering plants, reflecting their heterogeneity. The typical flower is a diploid plant because it has both male and female reproductive organs (pollen and fertilised eggs, respectively).

The FPA algorithm can be represented by the following four rules, depending on the biological process of pollination:

Pollinators follow Levy flight, and biotic and cross pollination can be considered as global pollination.

Abiotic self-pollination is used for local pollination.

Pollinators can achieve flower stability, which is the probability of reproduction. The latter is proportional to the degree of similarity between the two flowers in question.

The alternation between local and global pollination can be controlled by a probability $p \in [0,1]$.

During bio-pollination, pollinators can move pollen over long distances, providing the most suitable diversity and pollination for reproduction.

Mass vaccination can be represented follows:

$$x_i^{t+1} = x_i^t + L(x_i^t - g_*)$$

Where x_i^t the pollen or solution vector at iteration t , g_* the best solution found and L the pollination strength.

Since pollinators move long distances at different time intervals, Levy's flight can be an effective simulation of this feature, i.e. a value for L can be calculated:

Local pollination and flower stability can be represented as follows:

$$x_i^{t+1} = x_i^t + \varepsilon(x_j^t - x_k^t)$$

x_j^t and x_k^t : are pollens of different flowers of the same type of plant.

We simulated biotic and abiotic pollination, except that the percentage and frequency of each type of pollination were not taken into account. To model this function, we employ the switching probability, where the p -value indicates whether a change in the solution is the result of local selection or global gene flow.

B. Proposed method

Our approach is a rigid iconic registration method based on both FPA and BOA optimization methods. Figure 3 illustrates the different stages of our approach and which can be summarized as follows

- The first step of this section describes the set of images that we used in the registration process: We will perform a series of mono and multimodal medical image registration processes.
- The approach we have proposed aims to calculate the best rigid transformation (Tx, Ty, θ) which allows to correctly align the two images I_{ref} and I_{cib} .
- Selection of the best solution using the BOA and FPA optimizer: After the execution of the algorithms during a certain number of iterations; we obtain the best solutions obtained by each algorithm.
- To measure the correspondence between images. We used the similarity measures "Mean Squared Error" (MSE), "Mutual Information" (MI) and "Structural Similarity Index" (SSIM).
- In the last step we will compare the results obtained by the BOA algorithm with the results obtained by the FPA algorithm.

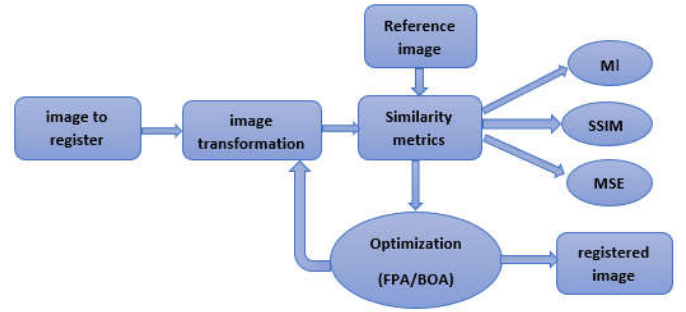


Figure 3: Diagram of the image registration process by BOA and FPA.

IV. COMPARATIVE AND EXPERIMENTAL RESULTS

This section is dedicated to a comparative study of Flower Pollination Algorithm (FPA) and Butterfly Optimization Algorithm (BOA).

In this comparative study, we have used the Whole Brain Atlas Database offered by the Harvard University Medical School [13]. CT, PET, and MRI are the available brain imaging techniques. There are three different MR images types that are taken into consideration: proton-density-weighted (PDW), T2-weighted, and T1-weighted (PD). Figures 4 present some test images.

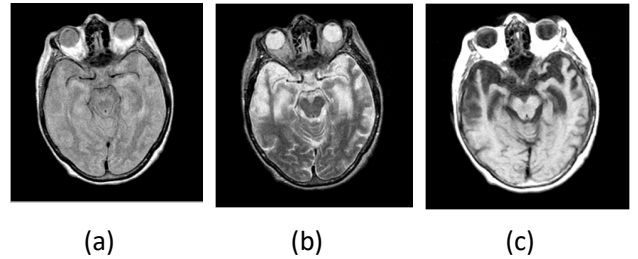


Figure 4: Reference and source images of IRM-PD, T2 and T1.

This section presents the findings of the experiments. Here, we report on our work analysing data from the Whole Brain Atlas. Quantitatively, using Iconic Similarity metrics, and qualitatively, using visual inspection, you can verify BOA and FPA performance.

A. Evaluation Metrics

Performance measures	Mathematical formulation
Feature mutual information (FMI)	$FMI = \frac{I_{FR}}{H_F + H_R} + \frac{I_{FS}}{H_F + H_S}$ $I_{FX} = \sum_{f,a} P_{EX}(i,j,p,q) \log_2 \frac{P_{FA}(i,j,p,q)}{P_F(i,j)cp_x(p,q)}$ <p>And H_x refer to the histogram-based entropies</p>
MSE	$MSE = \frac{1}{MN} \sum_{n=0}^M \sum_{m=1}^N [I_{ref} - I_{rec}]^2$
Structural similarity	$SSIM(x,y) = \frac{I(x,y) \cdot c(x,y) \cdot s(x,y)}{(2\mu_x\mu_y + c_1)(2\sigma_x\sigma_y + c_2)(cov_{xy} + c_3)}$ $= \frac{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)(\sigma_x\sigma_y + c_3)}{}$

Table 1 : Performance measures and their mathematical formulation

B. Comparison BOA with FPA

To begin, we ran a simulation with a set of MR images that included both single- and dual-modality components (T1/T1, T2/T2, PD/PD). Tables 1 and 2 show the results of both single- and multiple-modality registration.

1) Quantitative Comparison:

For monomodal and registration, we will consider images taken randomly from the Harvard database (IRM-T1/IRM-T1, IRM-T2/IRM-T2, IRM-PD/IRM-PD and CT/CT). These images have undergone a rigid transformation of $(\theta, T_x, T_y) = (5, 10, -10)$. The results of the different experiments are summarized in Tables 2,3,4 and 5. The color red indicates the best outcomes. According to these results, it can be seen that the BOA. We observe also that the FPA method is very fast compared to the BOA method.

At the second level, we tested the performance of the two algorithms, FPA and BOA. the results obtained are summarized in Tables 2,3,4 and 5.

According to these results, it can be seen that the BOA method offers good results compared to the FPA method.

	Estimated transformations				Error rate		
	Images	\hat{T}_x	\hat{T}_y	$\hat{\theta}$	EA_x	EA_y	EA_θ
BOA	T2-T2	-10.0254	10.0064	-4.9720	0.0254	0.0064	0.0280
	T1-T1	-9.9658	9.9831	-5.0234	0.0342	0.0169	0.0234
	PD-PD	9.9921	9.9530	-4.9992	0.0079	0.0470	0.0008
	CT-CT	-10.1702	10.3448	-4.9899	0.2838	0.1702	0.0101
FPA	T2-T2	-10.0158	10.1568	-4.9684	0.0158	0.1568	0.0316
	T1-T1	-9.9281	9.9819	-5.0900	0.0719	0.0181	0.0900
	PD-PD	-9.9906	9.9644	-4.9972	0.0094	0.0356	0.0028
	CT-CT	-9.6496	10.1284	-5.0093	0.3504	0.1284	0.0093

Table 2 : Monomodal image registration results (transformation estimation)

Images	BOA				FPA			
	SSIM	EQM	MI	Time	SSIM	EQM	MI	Time
T2-T2	0.9604	0.0002	1.3060	267.5600	0.9574	0.0004	1.3005	135.7105
T1-T1	0.9718	0.0026	1.3397	264.0453	0.9702	0.0032	1.3360	132.5687
PD-PD	0.9613	0.0013	1.3108	269.2868	0.9606	0.0017	1.3218	137.0041
CT-CT	0.9613	0.0010	1.3037	1250.2	0.9606	0.0017	1.3034	624.6

Table 3 : Monomodal image registration results (similarity measurement and computation time)

	Estimated transformations				Error rate		
	Images	\hat{T}_x	\hat{T}_y	$\hat{\theta}$	EA_x	EA_y	EA_θ
BOA	T1__T2	-9.9743	9.5360	-4.6387	0.0257	0.4640	0.3613
	T1__PD	-9.9849	9.6203	-4.7679	0.0151	0.3797	0.2321
	T2__T1	-9.9610	10.5232	-5.2406	0.0390	0.5232	0.2406
	T2__PD	-9.9755	10.0056	-5.0672	0.0245	0.0056	0.0672
	PD__T1	-9.9522	10.3069	-5.0984	0.0478	0.3069	0.0984
	PD__T2	-9.9916	9.8317	-4.7882	0.0684	0.1683	0.2118
FPA	T1__T2	-10.0532	9.4241	-4.5805	0.0532	0.5759	0.4195
	T1__PD	-10.0038	9.5845	-4.7872	0.0038	0.4155	0.2128
	T2__T1	-9.9260	10.6102	-5.3415	0.0740	0.6102	0.3415
	T2__PD	-9.9440	10.0663	-5.0260	0.0560	0.0663	0.0260
	PD__T1	-9.7530	10.4234	-5.1264	0.2476	0.4234	0.1264
	PD__T2	-10.0308	9.8451	-4.8985	0.0308	0.1549	0.1015

Table 4: Results of multimodal image registration (transformation estimation).

Images	BOA				FPA			
	SSIM	MSE	MI	Time	SSIM	MSE	MI	Time
T1_T2	0.9696	0.00007	1.3060	267.5600	0.9574	0.0004	1.3005	135.7105
T1_PD	0.9681	0.0005	1.3397	264.0453	0.9702	0.0032	1.3360	132.5687
T2_T1	0.9618	0.0061	1.3108	269.2868	0.9606	0.0017	1.3218	137.0041
T2_PD	0.9588	0.0018	1.3037	1250.2	0.9606	0.0017	1.3034	624.6

Table 5: Multimodal registration results (similarity measurement and calculation time)

2) *Qualitative Comparison:*

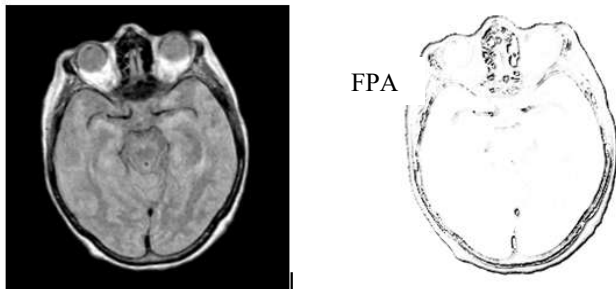
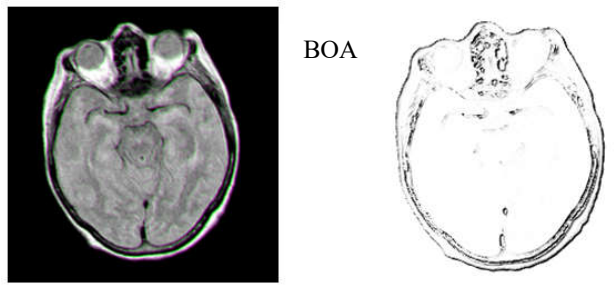
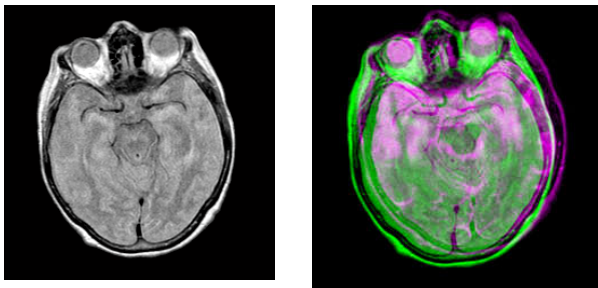


Figure 5 : Visual results for IRM PD –IRM-PD mono-modality image registration using BOA and FPA algorithms.

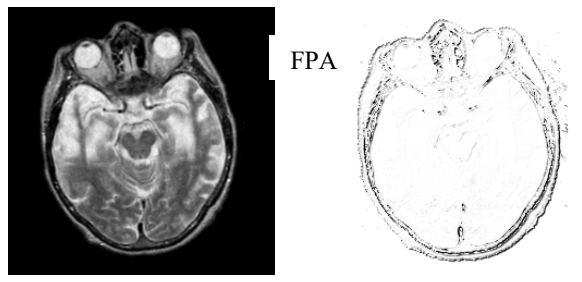
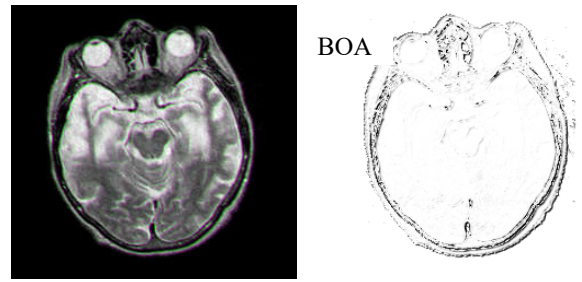
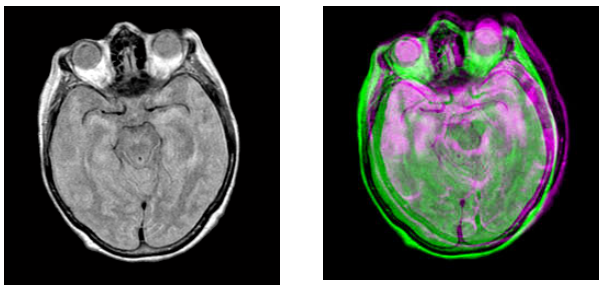


Figure 6 : Visual results for PD-T2 multi-modality image registration using BOA and FPA algorithms.

V. CONCLUSION AND FUTURE WORK

In order to improve the results obtained from meta-heuristic optimization algorithms in the iconic registration we have implemented these two algorithms. After running experiments to gauge the efficacy of various meta-heuristic optimization algorithms, it became clear that BOA was the most effective for both mono- and multi-modal image registration, with improved SSIM, EQM, and FMI indexes; however, the FPA method was noticeably quicker.

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