Improved Particle Swarm Optimization algorithm applied to rigid registration in medical images

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Abstract— **Image registration is a space-temporary correlation process that allows comparison and/or image matching. This process has value into medical area when it comes to compare images acquired by different modalities or in different times. In this work, we present a method based on computational intelligence techniques from Particle Swarm Optimization (PSO) algorithm, to seek the best answer (particle) exploring a solutions set (swarm). The algorithm we developed includes an original idea for starting and for avoiding local minimum values, in order to achieve good rigid registration results (scale, rotation, translation). The mono and multi modal registration are performed on 2D magnetic resonance imaging (MRI) in T1-T2 sequences and single-photon emission computed tomography (SPECT) images. Experimental results show better optimal solution and decrease in convergence time compared to PSO original algorithm.**

Keywords— **Image registration, Particle Swarm Optimization, Swarm Intelligence.**

I. Introduction

Medical image registration allows specialists obtaining full anatomy information through image comparison at the same or different modality and acquisition times. This process is used in medical treatment verification, illness monitoring (vigilance) and for constructing anatomic atlas from image information databases, among other applications [1, 2].

In this work, the registration process follows these characteristics: Dimensionality: 2D, Nature of transformation: rigid, Modalities: mono-modal, multi-modal and Optimization procedure: Swarm Intelligence [2, 3, 4].

We present a new perspective to improve image registration results through guided search and different similarity measures as fitness function. There are many works in PSO applied to registration [6, 7, 8, 11, 12].

This work is structured as follows: Section 2 describes the theoretical basis used. Section 3 sets out the comparison between PSO-original and PSO-improved algorithms. Section 4 presents and discusses the results obtained. Finally, Section 5 presents the main contributions and future work.

II. Image registration

A. Rigid Registration

Registration is the process for finding the best geometric alignment between two or more images at the same scene, the same or different modality, different time and/or different viewpoints. The involved images are called: *source* (target) and *floating* (reference) [2].

Registration aim is to find and apply geometric transformations on the reference image in order to modify pixels' coordinates, until the difference between the floating and target images is minimized through the definition of some measure of comparison. It can be written as:

$$I_R = T * I_F, \qquad (1)$$
$$M = \min(||I_O - I_F||)$$

where T is the geometric transformation, I_R is the modified image, I_F is the reference image, I_O is the target image and M is the measure of comparison.

In rigid registration, deformation occurs considering three parameters: scale, rotation and translation. To compute scale and translation, equation 2 shows the transformation matrix in 2D homogenous coordinates, where e_x and e_y is the scale and t_x and t_y defines the translation factor:

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} e_x & 0 & t_x \\ 0 & e_y & t_y \\ 0 & 0 & 1 \end{bmatrix} * \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \qquad (2)$$

In the same way, equation 3 shows the rotation transformation matrix, where α is the rotation angle:

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} Cos\ \alpha & Sin\ \alpha & 0 \\ -Sin\ \alpha & Cos\ \alpha & 0 \\ 0 & 0 & 1 \end{bmatrix} * \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \qquad (3)$$

B. Particle Swarm Optimization (PSO)

PSO is an algorithm that is part of the computational intelligence paradigm, which was initially inspired by the behavior of birds. PSO was developed by Kennedy and Eberhart in 1995, where important terms are defined such as a swarm and particles "flying" into a solution space [4].

Each particle is a parametric potential solution. PSO is an iterative algorithm where particles change their position in the parameter space through velocity. It is based on the best swarm behavior position and the best particle. To update the particle values, PSO seeks to minimize or maximize a target function called Fitness. Equation 4 defines PSO iterative operation:

$$V_i^{t+1} = WV_i^t + C_1R_1(P_{best} - X_i^t) + C_2R_2(g_{best} - X_i^t) \quad (4)$$

$$X_i^{t+1} = X_i^t + V_i^{t+1}$$

C. Similarity Measures

In registration, similarity measures allow quantizing difference between images. These measures should be based on probabilistic paradigms and they avoid analyzing pixel's information (intensity) directly, so it is an advantage because previously segmentation or feature extractions are not necessary [9].

Cross-Correlation (CC): is the ratio of the covariance to the product of standard deviations of two images. In this work, as usually done, we use the CC in mono-modal registration. The ideal alignment will produce CC = 1.

Mutual Information (MI): quantifies the statistical dependence between two variables based on individual entropies with the join entropy. MI is applied in multi-modal registration.

III. Proposed algorithm

Let us consider two images A and B, mathematical defined as $A, B : Z^2 => [0,255]$, where A is the target image and B is the reference image.

The proposed algorithm uses cross-correlation and mutual information for *Fitness* function. The procedure is summarized in the next stages:

1. Estimate initial Fitness function (FP) between inputs images A, B.
2. Initialize the swarm (X) in the initial solutions space composed by scale (E), translation (T) and rotation (R).

   $E = [E_{MIN}, E_{MAX}]$, $T = [T_{MIN}, T_{MAX}]$, $R = [R_{MIN}, R_{MAX}]$

   $$X_{i\to 1:N} = (X_i = rand[e,t,r] => e \in E \wedge t \in T \wedge r \in R)$$
   $$B^T{}_{i\to 1:N} = X_{i\to 1:N}\ B$$
   $$F_{i\to 1:N} = F\ (A, B^T{}_{i\to 1:N})$$
   $$If\ F_i > F_P => g_{Best} = X_i$$

   where B^T is the image after applying the geometric transformation, F is the Fitness function and g_{BEST} is the best particle among all swarm found by PSO.
3. According to particle $g_{Best} = [e_g, t_g, r_g]$, modify initial solutions in order to optimize the search. The next process is referred to scale but is similar in the case of translation and rotation:

   $$E_M = prom(E_{Min}, E_{Max})$$
   $$Si\ e_g > E_M => E_Y = [E_M, E_{Max}]$$
   $$else,\ E_Y = [E_{Min}, E_M]$$
   $$X_{i\to 1:N} = (X_i = rand[e,t,r] => e \in E_Y \wedge t \in T_Y \wedge r \in R_Y)$$
4. Considering the swarm X, the PSO algorithm avoids local minimum values, during the execution at specific iterations among randomize particles positions in solutions space.
5. Stop the algorithm after a given number of iteration.

Normally, PSO algorithm initializes with random particles of the swarm at the whole solutions space, which influences directly in the final solution, because searching is performed from the best parameters found according to algorithm heuristic. Oppositely, the proposed algorithm carries out guided search following the particle to improve initial *fitness*.

Introducing the previous modification, the heuristic of PSO algorithm is performed in a new reduced solution space, which makes possible obtaining a better result with low computational cost than in the original algorithm. Another change introduced is the randomization the particles after a specific number of iterations, which allow avoiding multiple local minimum values.

These proposed changes improve significantly the results of medical image registration as it will be presented in the next section.

IV. Results and discussion

In order to test the proposed algorithm, MR images in T1-T2 sequences are used for monomodal and multimodal registration with SPECT modality (Fig. 1). Reference images are generated with known values of scale, translation and rotation, so the performance of the algorithms can be estimated.

In the tests, we analyzed fitness values, processing times and errors achieved between target and registered image. In Fig. 2 we show mono modal registration results compared the original PSO and the proposed algorithm. Fitness values (CC) are shown, achieved with different particles and number of iterations. In the case of PSO algorithm, fitness reached around 0.4 and 0.7, as long as with proposed algorithm the fitness is constant in 0.7, being independent of particles values.

Fig. 3 shows computation times. In test 1 and 2, time for PSO algorithm is directly proportional to the number of iterations and particles' values. It is greater than 10 minutes, but with the proposed algorithm, time is significantly reduced. In test 1, PSO algorithm with 20 particles, and the proposed algorithm with 40 particles was considered, both using 50 iterations. In test 2, PSO algorithm with 50 particles, and the proposed algorithm with 60 particles was considered, always taking 50 iterations.

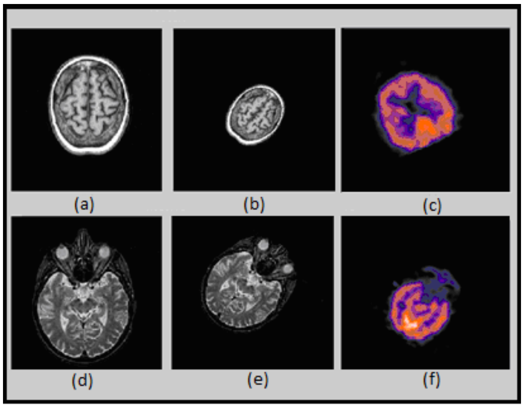

Fig. 1 Head images in MR modality **a)** Target image in T1 sequence; **b)** Reference image in T1 sequence **c)** Reference image in SPECT; **d)** Target image in T2 sequence **e)** Reference image in T2 sequence; **e)** Reference image in SPECT.

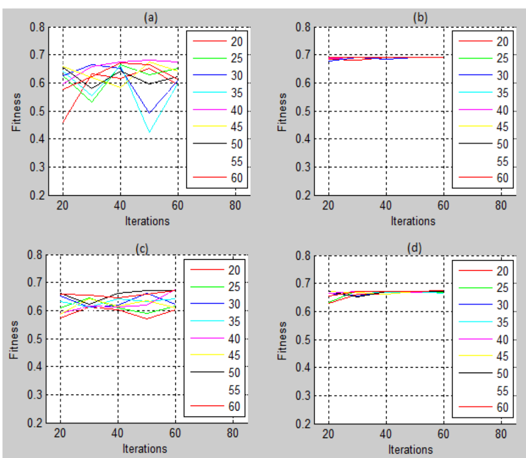

Fig. 2: Fitness vs. Iterations. a) PSO original, T1 image; b) Proposed algorithm; c) PSO original, T2 image; d) Proposed algorithm.

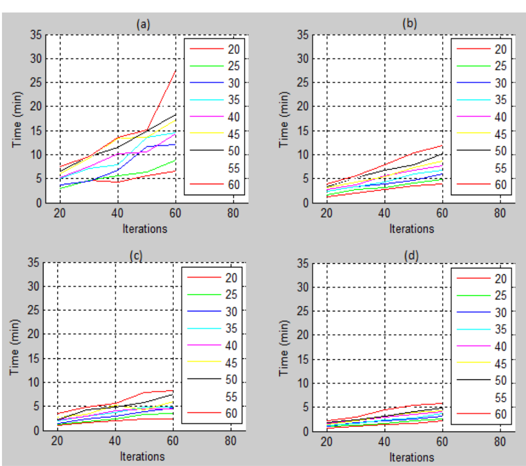

Fig 3: Time vs. iterations. a) PSO original, T1 image; b) Proposed algorithm; c) PSO original, T2 image; d) Proposed algorithm.

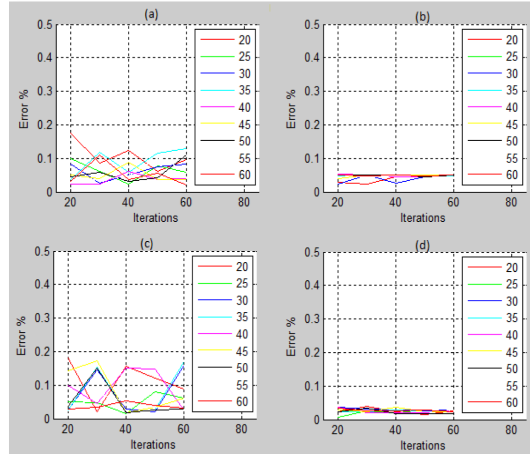

Fig. 4: Error vs. Iterations. a) PSO original, T1 image; b) Proposed algorithm; c) PSO original, T2 image; d) Proposed algorithm.

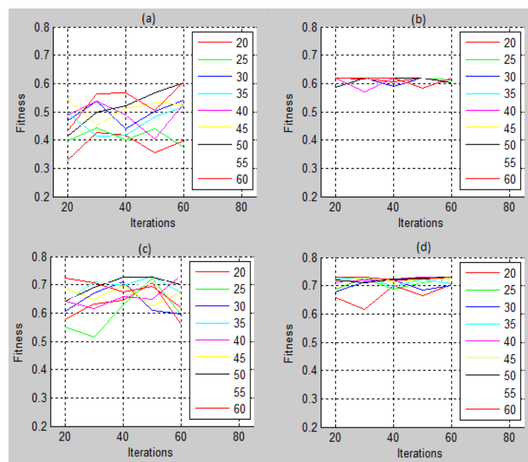

Fig 5: Fitness vs Iterations. a) PSO algorithm, T1-Spect; b) Proposed algorithm, T1-Spect; c) PSO algorithm, T2-Spect; d) Proposed algorithm, T2-Spect.

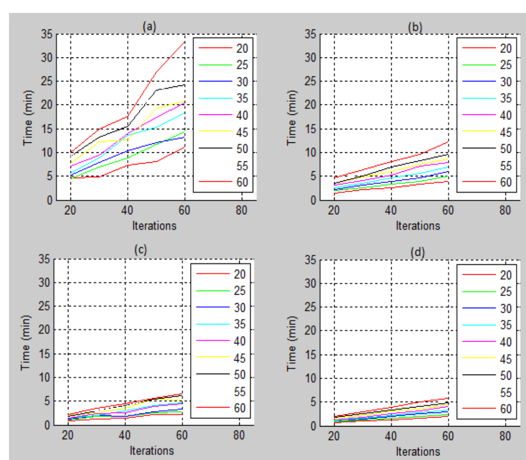

Fig 6: Time vs. iterations. a) PSO algorithm, T1-Spect; b) Proposed algorithm, T1-Spect; c) PSO algorithm, T2-Spect; d) Proposed algorithm, T2-Spect.

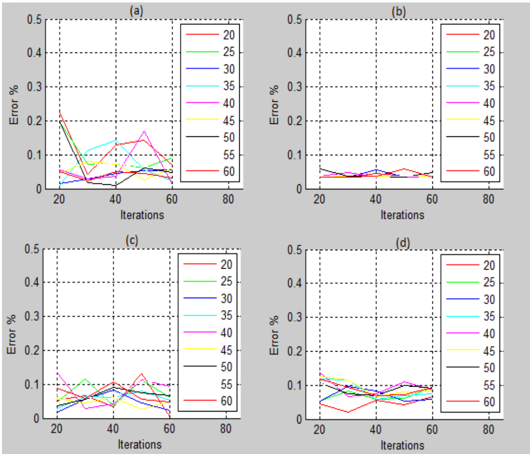

Fig 7: Error vs Iterations. a) PSO algorithm, T1-Spect; b) Proposed algorithm, T1-Spect; c) PSO algorithm, T2-Spect; d) Proposed algorithm, T2-Spect.

Fig. 4 shows the difference (hereby called Error) between target values of scale, rotation and translation and references, considering achieved values. The results show in the case of the proposed algorithm a difference less than 0.1%, compared with PSO results, where the difference changes according to iterations and particles number.

In the same way, the results of multimodal registration are shown in Fig. 5 to Fig. 7. The analysis is similar as the previous part.

V. Conclusion

In this work, we presented a new algorithm to register medical images through Swarm Intelligence. The proposed method based on PSO improves the rigid registration results; therefore we have shown that computational algorithms with collective behavior are useful to optimization procedures in images registration applications.

Considering this approach, we obtained better experimental results than those obtained with the original PSO algorithm in mono and multi modal registration. It improves the PSO performance, which allows stable and proper values for fitness function, computing time and error estimation, with previously known rotation, scale and translation values.

Using probabilistic measures leads to a fast processing, because it allows comparing image information directly without previous segmentation or feature extraction.

It is always necessary to reduce computational resources and processing time. Swarm Intelligence paradigm has shown to be useful in optimization problems and in medical image registration, as it provided significant improved results.

Future work is focused in 2D and 3D registration including also affine and projective registration, which is required in muscular and abdominal imaging. We aim to develop faster and "smarter" algorithms to be used in different applications.

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