An Approach to Multimodal Biomedical Image Registration Utilizing Particle Swarm Optimization

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Overview

1. Introduction

- Fuse different image modalities → Registration
- Intensity based approach
  - Search space
  - Similarity metric
  - Search strategy →PSO as global optimization approach
- They propose a PSO improvement for registration

2. Image Registration Process

- Rigid body transformations

A. Similarity Metric

Normalized Mutual Information I_N→ global optimization

B. Optimization of the Metrics

Global <> Local

3. Image Registration using PSO

A. Modifications to the PSO Algorithm

B. PSO Approach for Registration Utilizing Initial Position

I. Hybrid PSO with crossover

II. Hybrid PSO with crossover and subpopulations

III. PSO with constriction coefficient and relaxed convergence criteria.

4. Methods

A. Data

B. Initial Orientations

C. Registration Controls

D. Optimization Technics

I. Accuracy

II. Efficiency

ES1…ES7

PSO1…PSO8

5. Results

A. Accuracy

B. Efficiency

6. Discussion

Prior knowledge of the location of the global optimum.

4. Conclusion

PSO

- In PSO, at each iteration, the ith particle $x_i, i = 1 \dots, N$, (N is the number of particles) moves by addition of a velocity vector v_i, which is a function of the best position (the position attaining the lowest objective function value) found by that particle, ($\mathbf{p}_i$, for personal best) and of the best position found so far among all particles ($\mathbf{g}$, for global best).

$$\begin{cases} \mathbf{v}_i(t) = w(t)\mathbf{v}_i(t-1) + \varphi_1 u_1 \left(\mathbf{p}_i - \mathbf{x}_i(t-1)\right) \\ \qquad + \varphi_2 u_2 \left(\mathbf{g} - \mathbf{x}_i(t-1)\right) \\ \mathbf{x}_i(t+1) = \mathbf{x}_i(t) + \mathbf{v}_i(t) \end{cases} \tag{5}$$

where $w(t)$ is the *inertial weight*, the φ are *acceleration constants*, and the $u \in (0,1)$ are uniformly distributed random numbers.

Modifications to the PSO Algorithm

1. Mutation and crossover (add ES/GA operators)

$$\mathbf{x}_i' = p\mathbf{x}_i + (1-p)\mathbf{x}_j$$
$$\mathbf{x}_j' = p\mathbf{x}_j + (1-p)\mathbf{x}_i$$
$$p \sim \mathrm{UNIF}(0,1).$$

2. Group the particles into subpopulations

k-means clustering

2. Constriction coefficient

$$\mathbf{v}_i(t) = \chi\left[\mathbf{v}_i(t-1) + \varphi_1 u_1\left(\mathbf{p}_i - \mathbf{x}_i(t-1)\right) + \varphi_2 u_2\left(\mathbf{g} - \mathbf{x}_i(t-1)\right)\right] \quad (10)$$

$$\chi = \frac{2\kappa}{|2-\varphi-\sqrt{\varphi^2-4\varphi}|}$$
$$\varphi = \varphi_1 + \varphi_2, \quad \varphi > 4, \quad \kappa \in [0,1]. \quad (11)$$

PSO Approach for Registration Utilizing Initial Position

- Users of biomedical image registration systems can choose an accurate initial transformation. x_{init}

$$\mathbf{v}_i(t) = w(t)\mathbf{v}_i(t-1) + \varphi_1 u_1 (\mathbf{p}_i - \mathbf{x}_i(t-1)) + \varphi_2 u_2 (\mathbf{g} - \mathbf{x}_i(t-1)) + \varphi_3 u_3 (\mathbf{x}_{\text{init}} - \mathbf{x}_i(t-1)) \qquad (12)$$

where φ_3 is the acceleration constant for the return to the initial orientation. Similarly, (10) can be modified to

$$\mathbf{v}_i(t) = \chi [\mathbf{v}_i(t-1) + \varphi_1 u_1 (\mathbf{p}_i - \mathbf{x}_i(t-1)) + \varphi_2 u_2 (\mathbf{g} - \mathbf{x}_i(t-1)) + \varphi_3 u_3 (\mathbf{x}_{\text{init}} - \mathbf{x}_i(t-1))] \qquad (13)$$

$$\chi = \frac{2\kappa}{|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}|}$$

$$\varphi = \varphi_1 + \varphi_2 + \varphi_3, \quad \varphi > 4, \quad \kappa \in [0, 1]. \qquad (14)$$

PSO Approach for Registration Utilizing Initial Position

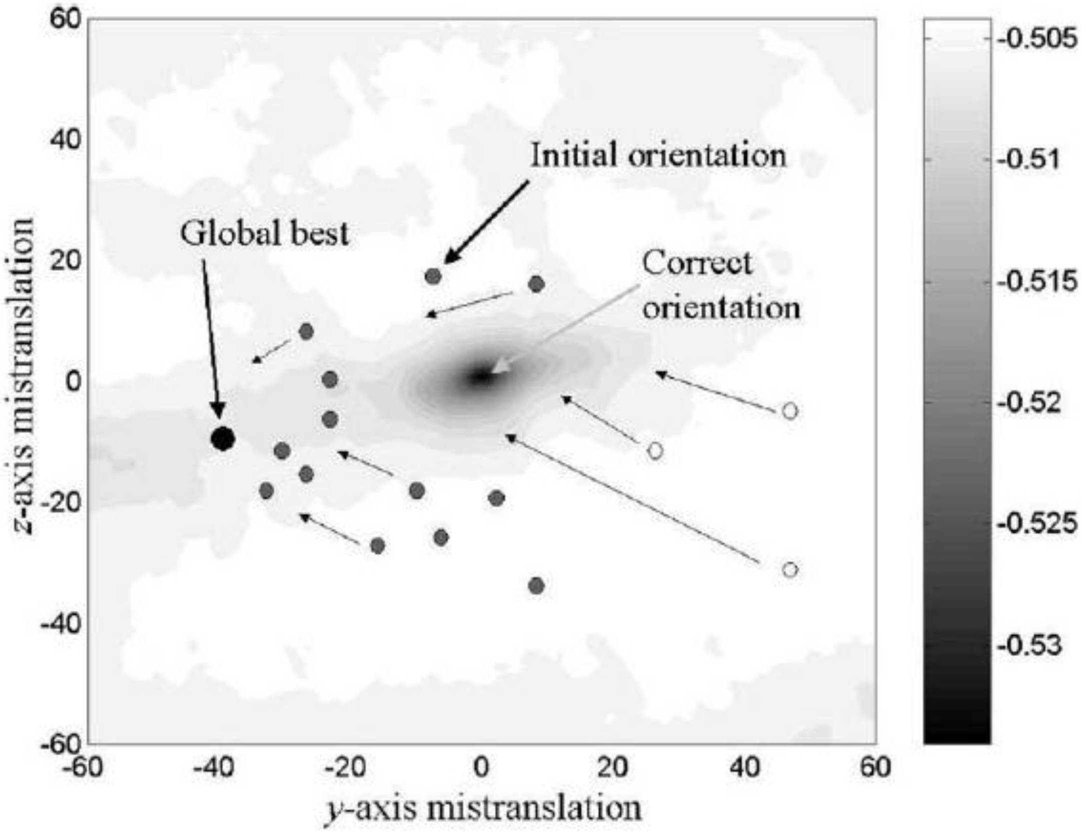


Fig. 4. Illustration of the proposed PSO algorithm utilizing initial position. The contours represent the normalized mutual information landscape of 2-D US to 3-D histological registration. The current global best position g is in the area of a local minimum. Although the particles begin to swarm around g, some of the particles (white circles) are veered slightly toward the point representing the initial orientation, and would eventually find the "basin of attraction" for the global minimum.

PSO Approach for Registration Utilizing Initial Position

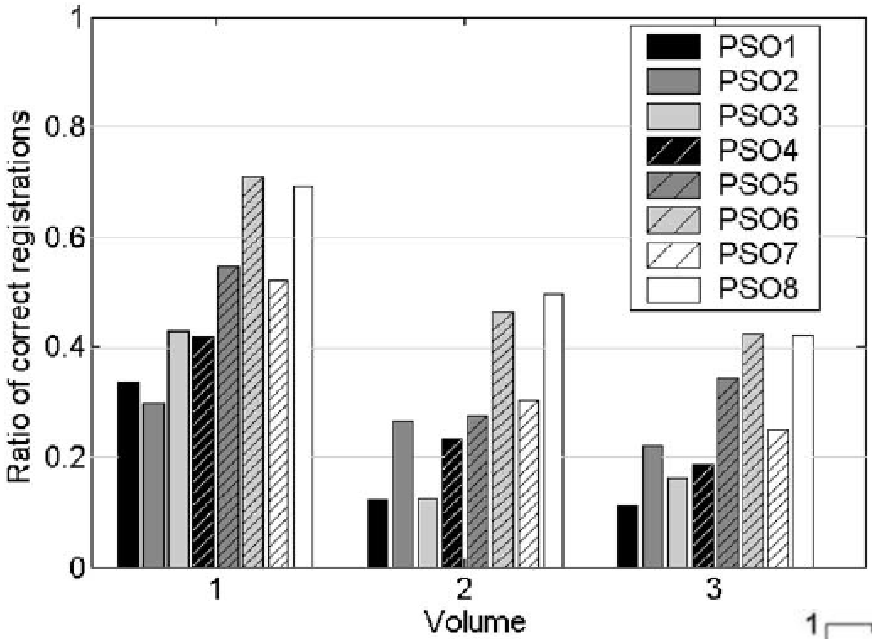
- It was found that the PSO-ES hybrid and PSO incorporating the constriction coefficient produced the highest percentage of correct registrations among all PSO techniques tested.

  Therefore, the modification utilizing the initial orientation was applied to those methods, resulting in three algorithms.

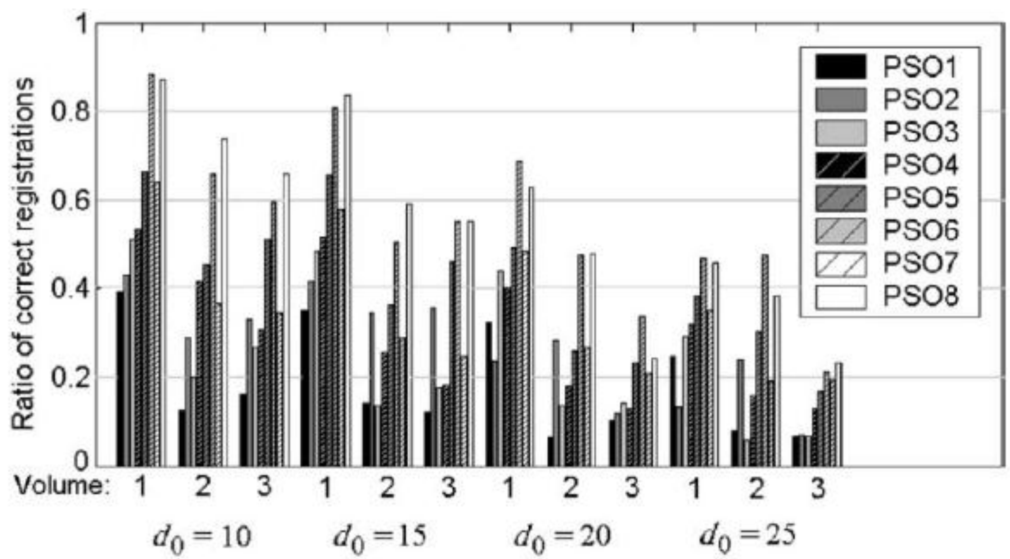
Methods

- Data
  - Obtained through the NLM-NIH Visible Human Project
  - BrainWeb database at McGill University
- Initial Orientations
  - In the registration experiments, each 2-D image was oriented at 10, 15, 20, and 25 voxels from ground truth translation.
- Registration Controls
  - Normalized mutual information was computed by using 64 histogram bins
- Optimization Techniques
  - Eight PSO techniques were used to perform the registrations. For comparison, registrations were also performed on seven ES techniques.
  - Results were compared on the following merit measures:
    1. Accuracy, as measured by the ratio of correct registrations to all registrations. A registration is considered to be correct if the Euclidean distance from the ground truth translation and final translation is less than 2 voxels, and if the maximum absolute value of the three rotation errors is less than 2^{o} .
    2. Efficiency, as measured by the mean number of function evaluations for correct registrations for each 2-D image registered to a 3-D volume.

Results



Ratio of correct registrations
Volume
1
2
3
0
0.2
0.4
0.6
0.8
PSO1
PSO2
PSO3
PSO4
PSO5
PSO6
PSO7
PSO8



Ratio of correct registrations
Volume: 1 2 3 1 2 3 1 2 3 1 2 3
$d_0 = 10$
$d_0 = 15$
$d_0 = 20$
$d_0 = 25$
0
0.2
0.4
0.6
0.8
PSO1
PSO2
PSO3
PSO4
PSO5
PSO6
PSO7
PSO8

Results

TABLE II
MEAN NUMBER OF FUNCTION EVALUATIONS ($\times$ 1000) FOR ES AND PSO TECHNIQUES.
THE THREE MOST ACCURATE ES AND PSO TECHNIQUES ARE SHOWN IN BOLDFACE

Volume	Algorithm	$d_0 = 10$	$d_0 = 15$	$d_0 = 20$	$d_0 = 25$
US – Hist.	**ES1**	**2.26±20.394**	**2.154±0.294**	**2.382±0.353**	**2.341±0.423**
	ES2	**2.128±0.383**	**2.299±0.414**	**2.204±0.388**	**2.333±0.360**
	ES3	**2.169±0.390**	**2.171±0.366**	**2.272±0.496**	**2.245±0.418**
	ES4	1.131±0.229	1.094±0.158	1.135±0.211	1.159±0.143
	ES5	1.123±0.209	1.216±0.204	1.269±0.194	1.158±0.206
	ES6	0.816±0.155	0.831±0.148	0.835±0.113	0.842±0.071
	ES7	0.821±0.154	0.817±0.172	0.760±0.146	0.852±0.473
	PSO1	1.889±0.195	1.824±0.191	1.801±0.201	1.995±0.000
	PSO2	1.294±0.235	1.337±0.272	1.397±0.278	1.501±0.271
	PSO3	2.754±0.999	3.202±0.828	2.415±0.888	3.121±0.800
	PSO4	2.543±0.544	2.351±0.472	2.429±0.561	1.970±0.281
	PSO5	**1.802±0.546**	**1.689±0.450**	**2.125±0.706**	**2.379±0.776**
	PSO6	**3.467±0.683**	**3.765±0.849**	**3.502±0.801**	**3.650±0.629**
	PSO7	3.674±0.048	3.660±0.015	3.698±0.139	3.550±0.523
	PSO8	**2.367±0.601**	**2.449±0.705**	**2.674±0.641**	**2.736±0.687**

Discussion

- The proposed modifications to the velocity update were designed specifically for **image registration**.

- Similarity metric functions are often characterized by many **local optima**. Although the **constriction coefficient** prevents the particles from straying out of the space of feasible solutions, the particles have a greater probability of being drawn out of local optima by the additional **X_o term**.

- Although this term improved registration accuracy, in other applications, there may be **no prior knowledge** of the location of the **global optimum.**