# Chapter 84
# Research of Medical Image Registration Based on RMI-SAPSO Algorithm

**Danyang Zhao, Benqiang Yang, Libo Zhang, Xiangrong Zhou, Yenwei Chen, Hiroshi Fujita and Huiyan Jiang**

**Abstract** Aiming at avoiding misregistration in complicated medical image registration based on mutual information-simulated annealing particle swarm optimization (MI-SAPSO), we propose a novel algorithm named regional mutual information-simulated annealing particle swarm optimization (RMI-SAPSO). This method uses wavelet decomposition to denoise images, then determines optimum transformation parameters under choosing regional mutual information as objective function, finally does spatial geometric transformation according to the parameters to register medical images. Experimental results showed that the proposed method can register medical images effectively. It has a good robustness and owns better precision than traditional algorithm.

**Keywords** Medical image registration · Wavelet decomposition · PSO algorithm · SA algorithm · Regional mutual information

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D. Zhao (✉) · H. Jiang
Software College, Northeastern University, Shenyang, Liaoning, China
e-mail: hyjiang@mail.neu.edu.cn

B. Yang · L. Zhang
Radiology Department, PLA General Hospital, Shenyang, Liaoning, China

X. Zhou · H. Fujita
Graduate School of Medicine, Gifu University, Gifu, Japan

Y. Chen
Department of Information Science and Engineering,
Ritsumeikan University, Shiga, Japan

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## 84.1 Introduction

With the development of modern computer technology and digital medical equipment, digital image in medicine has been one of the most important methods in disease diagnosis for clinicians and experts. Medical image registration has important guiding significance for computer-aided diagnosis (CAD). Registration accuracy impacts the quality of feature extraction and diagnosis of the CAD system directly. Therefore, improving the accuracy of image registration has important application value for clinical medical research.

For medical image registration method, it is divided into 2D and 3D registration, rigid registration and nonrigid registration, single-mode image registration and multimodality image registration according to dimension of images, image space transformation model, and the mode of imaging, respectively. Among them, feature-based registration and gray-based registration are most widely used. The accuracy of feature-based registration is limited by feature points. However, gray-based image registration does not. Therefore, this chapter will improve gray-based image registration algorithm.

The optimization algorithm and a suitable objective function are very important in the gray-based image registration algorithm. At present, commonly used optimization algorithms are genetic algorithm (GA) [1], Powell Algorithm [2], simulated annealing (SA) [3], particle swarm optimization (PSO) [4, 5], etc. These optimization algorithms can optimize objective function well, but they still have some problems. For example, the algorithm based on PSO is easily trapped into local optimal solution; the performance of SA algorithm is sensitive to parameters and has a slow rate of convergence. Therefore, we should consider the problems of both global and local. For measurement function, most image registration using mutual information as objective function can implement registration process simply and quickly. But it is lack of spatial information, which will lead to misregistration. Furthermore, mutual information is very sensitive to the changes of the overlap region, which is the reason for misregistration [6].

Aiming to overcome these blemishes, we propose a medical image registration algorithm based on regional mutual information and SAPSO hybrid optimization (RMI-SAPSO). It chooses regional mutual information as objective function first, and then uses SAPSO to optimize the regional mutual information, which can improve image registration accuracy.

## 84.2 Related Technologies

### *84.2.1 Regional Mutual Information*

Regional mutual information is mutual information that introduces spatial information. During calculation, it regards image as multidimensional point set of distribution, each point not only presents pixel values, but also its neighborhood. Thus, the obtained image information by this method is accurate, the registration results are smoother, and robustness is also enhanced. From the view of time complexity, the time complexity of RMI and MI will eventually converge to $O(n^2)$ [7].

The calculation of regional mutual information is shown as formula (84.1).

$$\mathrm{RMI} = H_g(C_R) + H_g(C_F) - H_g(C) \tag{84.1}$$

Among them, $C$ is the covariance matrix, $H_g(C) = \log_2((2\pi e)^9 \det(C)^{\frac{1}{2}})$ represents the corresponding joint entropy, $H_g(C_R)$ is the corresponding marginal entropy of image $R$, which is gained from calculating the $9 \times 9$ matrix in the upper left corner of the covariance matrix, $H_g(C_F)$ is the corresponding marginal entropy of image $F$, which is gained from calculating the $9 \times 9$ matrix in the upper right corner of the covariance matrix.

### 84.2.2 Hybrid SAPSO Algorithm

Due to traditional PSO algorithm's shortcomings, a new mechanism was proposed. This mechanism can make the algorithm jump out of the local optimal position with a greater probability and enter into other areas of the space for searching.

The formulas of SAPSO hybrid algorithm to the particle's location and speed optimization are shown as formulas (84.2), (84.3), and (84.4).

$$x_{i,d}^{k+1} = x_{i,d}^{k} + v_{i,d}^{k} \tag{84.2}$$

$$\begin{aligned} v_{i.d}^{k+1} = {} & \mathrm{sign}(f(x^{k+1}) - f(x^k))w \times v_{i,d}^{k} \\ & + c1 \times r1 \times (p_{i,d}^{k+1} - x_{i,d}^{k+1}) + c2 \times r2 \times (p_{g,d}^{k+1} - x_{i,d}^{k+1}) \end{aligned} \tag{84.3}$$

$$\mathrm{sign}(x) = \begin{cases} 1 & x \geq 0 \\ -1 & x < 0 \ \text{ and } \mathrm{rand}() < \exp(\frac{x}{t_k}) \end{cases} \tag{84.4}$$

In formulas (84.2) and (84.3), $i$ is particle's serial number and $i = 1, 2, \ldots, M$, $M$ is the number of initial particles, $d$ is the serial number of the $N$ dimensional coordinates of each particle, $k$ is the subcode of particle, and $c_1, c_2$ are non-negative constants, $r_1, r_2$ are the random number during $[0, 1]$, $v_{\min}, v_{\max}$ are the minimum and maximum speed and $v_{id} \in [v_{\min}, v_{\max}]$, $w$ is the inertia factor. In formula (84.4), $\mathrm{sign}(x)$ is the probability function of particles' position transferring, which is obtained in terms of Metropo1is [8] criterion based on simulate anneal arithmetic, and $t_k$ is the control parameter.

## 84.3 RMI-SAPSO-Based Medical Image Registration

For RMI-SAPSO-based medical image registration, first it denoises the reference image and floating image and initializes images after pretreatment. Then it iterates RMI-SAPSO algorithm and completes the image registration according to the optimal transformation parameters determined by the algorithm. Finally it outputs image registration results. Summary of the proposed algorithm is shown in Fig. 84.1.

### *84.3.1 Image Denoising Based on Wavelet Decomposition*

This paper uses the wavelet shrinkage algorithm [9] for image denoising. Threshold function is mainly divided into the hard threshold function and the soft threshold function. Although the hard threshold method can be better to retain the image edge features, the processed image will appear visual distortion of the ring, etc. However, the results of the soft threshold method are relatively smooth, so we use the wavelet shrinkage algorithm based on the soft threshold method for denoising.

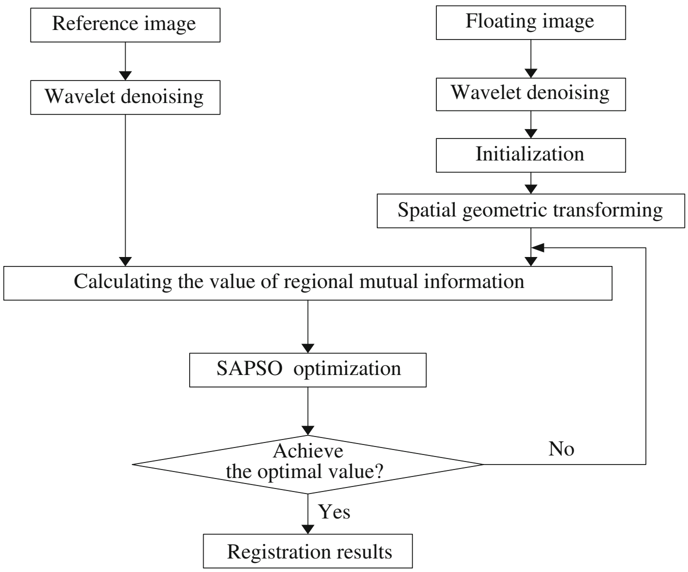


**Fig. 84.1** RMI-SAPSO image registration process

### 84.3.2 RMI-SAPSO-Based Medical Image Registration Algorithm

After denoising, we do a series of initial operation including determining the population size of SAPSO algorithm, setting the initial point of the search process and the initial search direction, and determining the initial temperature in the SA algorithm.

The pixels in images do spatial geometric transformation according to the transformation parameters from the optimize algorithm. And spatial geometric transformation is shown as formula (84.5).

$$
\begin{aligned}
T(x) &= Rx + t \\
&= \begin{pmatrix} \cos\beta\cos\gamma & \cos\alpha\sin\gamma + \sin\alpha\sin\beta\cos\gamma & \sin\alpha\sin\gamma - \cos\alpha\sin\beta\cos\gamma \\ -\cos\beta\sin\gamma & \cos\alpha\cos\gamma - \sin\alpha\sin\beta\sin\gamma & \sin\alpha\cos\gamma - \cos\alpha\sin\beta\sin\gamma \\ \sin\beta & -\sin\alpha\cos\beta & \cos\alpha\cos\beta \end{pmatrix} \\
&\quad \begin{pmatrix} x \\ y \\ z \end{pmatrix} + \begin{pmatrix} t_x \\ t_y \\ t_z \end{pmatrix}
\end{aligned} \tag{84.5}
$$

where $\alpha, \beta, \gamma$ are rotation angles around each axis and $t_x, t_y, t_z$ are translations around each axis, respectively.

RMI-SAPSO optimization algorithm processes are described as follows:

Step1: (initialization) Select population size $m$, and for the particles of each population $i, \cdots i = 1, 2 \cdots m$

Step 1.1: Initialize $x[i]$ as the position of the particle $i$ of population;

Step 1.2: Take the result of calculating $fitness[i]$ as the fitness value of particle $i$. The fitness value is the regional mutual information of the two images;

Step 1.3: Initialize $v[i]$ as the velocity of particle $i$;

Step 1.4: Initialize *gbest* with the particle which has the best fitness value in the population;

Step 1.5: Initialize $pbest[i]$with $x[i]$and initialize $pbest\_fitness[i]$ with $fitness[i]$;

Step 2: Iterate $i = i + 1$ until meeting the termination condition of the algorithm, and then stop iteration to implement step 3.

Step 2.1: Calculate the current value of $x[i]$ according to formula (84.2);

Step 2.2: Do spatial geometric transformation for each particle and statistic the joint histogram by using image interpolation algorithm. After that, calculate the regional mutual information $fitness[i]$;

Step 2.3: Estimate and process the local best position of each particle. If $fitness[i] > pbest_fitness[i]$then $pbest\_fitness[i] = fitness[i]$ and $pbest[i] = x[i]$;

Step 2.4: Search *gBest* and if $pbest\_fitness[i] > pbest\_fitness[gBest]$ then $gBest = x[i]$;

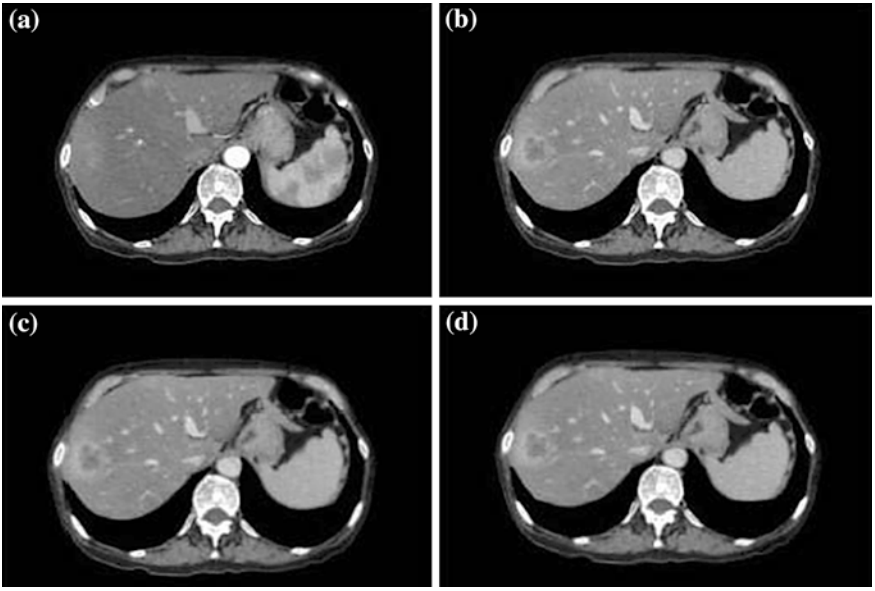


**Fig. 84.2** Registration results of the two algorithms

Step 2.5: Judge the number of iterations. If the number of iterations is 1, then give the initial temperature $t_0$ and determine the coefficient of temperature degradation. If the number of iterations is greater than 1, then calculate the current temperature according to $t_{k+1} = a * t_k$;

Step 2.6: Calculate the speed of each particle according to formula (84.3) and formula (84.4);

Step 3: Output the global optimal solution and use it to do spatial geometric transformation for the floating image. Finally, output the registration results.

## 84.4 Experimental Results and Analysis

The medical image data used in the experiment are all abdominal CT images from a domestic large hospital. Among them, the resolution between the layers of the reference image and floating image ranges from 0.9 to 3 mm, and the resolution within the layers is 512 × 512. The data are all DICOM data and the bit depth is 12. The platform for experiments is MATLAB R2008a.

The experimental results are shown as Fig. 84.2, where (a) and (b) represent the reference image and floating image after denoising respectively, (c) is registration result of traditional SAPSO algorithm, (d) is registration result of the proposed RMI-SAPSO algorithm.

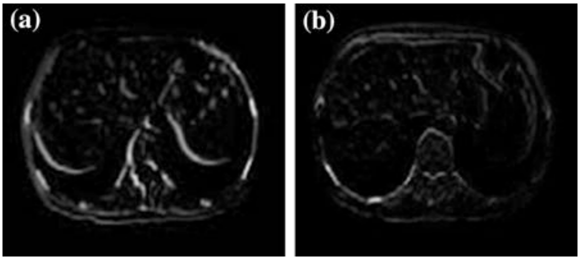


**Fig. 84.3** Image of gray difference

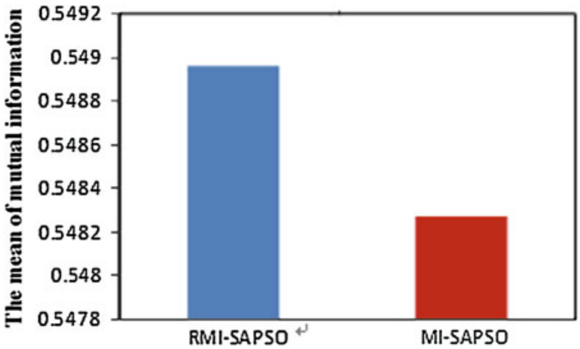


**Fig. 84.4** Contrast of RMI-SAPSO and MI-SAPSO registration

Figure 84.3 shows the gray level difference between the two registration algorithms' results and the original image. Among them, (a) is the gray level difference between the result of the traditional SAPSO algorithm and the original image and (b) is the gray level difference between the result of the proposed RMI-SAPSO algorithm and the original image.

In this paper, we use mutual information value as an evaluation criterion to quantitatively compare the traditional MI-SAPSO algorithm with the proposed RMI-SAPSO algorithm and the results are shown as Fig. 84.4.

Figure 84.4 represents mean of the algorithm's mutual information. Through the contrast, it can be seen that the mean value of the proposed RMI-SAPSO registration algorithm is higher than that of the traditional MI-SAPSO registration algorithm and it has a good robustness. It is thus clear that the proposed algorithm can effectively improve the accuracy of the registration.

## 84.5 Conclusions

The proposed RMI-SAPSO medical image registration algorithm increases the extraction of the spatial information through introducing the regional mutual information and improves the registration accuracy of the local area of the image. Experimental results show that this registration algorithm can effectively improve the accuracy of abdominal CT image registration with good robustness. It can solve the problem of misregistration in a complex medical image registration.

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## References

1. Cross ADJ, Wilson RC, Hancock ER (1996) Genetic search for structural matching. In: Computer vision-ECCV'96, vol 1064(15), pp 514–525
2. Maes F, Collignon A, Vandermeulen D et al (1996) Multi-modality image registration by maximization of mutual information. IEEE Trans on Med Imaging 16(19):187–198
3. Liu A, Pizer S, Eberly D et a1 (1994) Volume registration using the 3D core. In: Proceeding of SPIE, vol 2359(19), pp 217–226
4. Kennedy J, Eberhart R (1995) Particle swarm optimization. In: ICNN, vol 16(11), pp 1942–1948
5. Eberhart R, Kennedy J (1995) A new optimizer using particle swarm theory. In: MHS'95, vol 18(13), pp 456–459. doi: 10.1109/MHS 494215
6. Studholme C, Hill DLG, Hawkes DJ (1999) An overlap invariant entropy measure of 3D medical image alignment. Pattern Recogn 32(17):71–86
7. Russakoff DB, Rohlfing T, Shahidi R et al (2004) Image similarity using mutual information of regions. In: Proceedings of ECCV, vol 3023(16), pp 596–607
8. Metropolis N, Rosenbluth AW, Rosenbluth MN et al (1953) Equations of state calculations by fast computing machines. J Chem Phys 21(9):1087–1092
9. Donoho DL (1995) De-noising by soft-thresholding. IEEE Trans on IT 41(5):613–627