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BIOMEDICAL IMAGE REGISTRATION BASED ON FRUIT FLY OPTIMIZATION ALGORITHM WITH SEGMENTED MUTATION AND POWELL

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Abstract. *Aiming at the shortcoming that the fruit fly optimization algorithm (FOA) is easy to fall into local extremum, we come up with segmented mutation, and introduce segmented mutation into FOA, and then fruit fly optimization algorithm with segmented mutation (FOA-SM) is put forward. On the issue of biomedical image registration, mutual information is as the similarity measure, and we combine FOA-SM and Powell for biomedical image registration. Finally, a method based on FOA-SM and Powell for biomedical image registration is proposed. Simulation results show that our method has advantages of fast calculating speed, high precision and strong robustness. It is a kind of efficient automatic image registration method and has good clinical value.*
Keywords: Segmented mutation, Fruit fly optimization algorithm (FOA), Powell, Mutual information, Biomedical image registration

1. **Introduction.** The process of biomedical image registration is to transform an image pixel space position and make it with another image pixel space position alignment. Currently, the biomedical image registration has been widely used in biomedical clinical applications, such as radiation treatment planning, operation guide, imaging movement calibration, disease diagnosis, image segmentation and tracking check of treatment effect [1-3]. Biomedical image registration has three core selection problems: searching space of registration, similarity measure and optimization method. The registration result is mainly affected by optimization method, so the selection of optimization method is very important. At present, more mature biomedical image registration methods are classical simplex method and Powell method [4]. Besides that, there are heuristic optimization algorithms such as the improved genetic algorithm (GA) [5], ant colony optimization (ACO) [6] and particle swarm optimization (PSO) [7]. These methods all have some disadvantages. For simplex method, the highest point and the lowest point are firstly confirmed, the better point is solved through reflection method, extension method and compression method, next the highest point is displaced by this better point, new simplex method is made to approach to minimum point, and its defect is too slow convergent speed. Powell method is modified coordinate rotation algorithm, starts from the initial point, alternately executes linear search along the axis direction, and is easy to fall into local extremum. The above several heuristic optimization algorithms can adaptively optimize registration parameters, and all have disadvantages such as complex algorithm implementation and lots of parameters.

Fruit fly optimization algorithm (FOA) is that a new type of heuristic optimization algorithm which mimics natural fruit flies crowd behavior was proposed by Taiwan scholar Dr. Pan in 2011 [8]. FOA is easy to realize, has few parameters and is easy to transplant. So far, the FOA has been applied in mathematical function extremum [9], coefficient of fine-tuning Z-SCORE mode [9], parameter optimization of generalized regression neural network (GRNN) [10] and parameter optimization of support vector machine (SVM) [11], etc. FOA is gradually becoming a new bright spot in the field of heuristic optimization algorithm. However, like other heuristic optimization algorithms, FOA is very easy to fall into local extremum, and has slow convergence speed and low convergence precision.

To solve the problem that the shortcoming of FOA is easy to fall into local extremum, we come up with fruit fly optimization algorithm with segmented mutation (FOA-SM). On the issue of biomedical image registration, we select mutual information as registration similarity measure and combine FOA-SM and Powell for biomedical image registration. This paper is organized as follows. Fruit fly optimization algorithm with segmented mutation (FOA-SM) is put forward in Section 2. Biomedical image registration based on FOA-SM and Powell is come up with in Section 3. Simulation results and analyses are given in Section 4. The paper is concluded by Section 5.

2. **Fruit Fly Optimization Algorithm with Segmented Mutation (FOA-SM).**

2.1. **Segmented mutation.**

Definition 2.1. *(segmented mutation effectiveness coefficient ε) ε indicates sustained degree of segmented mutation efficiency, see Formula (1).*

$$\varepsilon = \begin{cases} 1 & 1 \le g \le \mu \\ \sqrt{\left(\left|\frac{G^\alpha - g^\alpha}{G^\alpha}\right|\right)^{\frac{1}{\alpha}} \times \left(\left|\frac{g^\alpha - G^\alpha}{G^\alpha}\right|\right)^{\frac{1}{\alpha}}} & \mu < g \le G \end{cases} \tag{1}$$

In Formula (1), g is the current number of iteration and G is the maximum number of iteration. When the value of g is between 1 and μ, the value of ε is 1. When the value of g is between μ and G, the value of ε is a diminishing value between 1 and 0. When the value of g is G, the value of ε is 0. The higher the value of ε is, the greater the mutation efficiency is. In this paper, according to experimental experience value, the value of μ is 15, the value of α is 1.618.

Definition 2.2. *(segmented mutation factor ξ) Segmented mutation factor ξ indicates that the algorithm executes different mutation operation at different evolution stages. The calculation of ξ is shown in Formula (2). The calculation of segmented mutation control points Δ is shown in Formula (3), Formula (4) and Formula (5). The value of β is the point of golden section (0.618) in Formula (3), Formula (4) and Formula (5).*

$$\xi = Cauchy(0,1) \times \Delta_1 + T(g) \times \Delta_2 + N(0,1) \times \Delta_3 \tag{2}$$

$$\Delta_1 = \begin{cases} 1 & 1 \le g < (1-\beta)G \\ 0 & (1-\beta)G \le g < (1-\beta)(1+\beta)G \\ 0 & (1-\beta)(1+\beta)G \le g \le G \end{cases} \tag{3}$$

$$\Delta_2 = \begin{cases} 0 & 1 \le g < (1-\beta)G \\ 1 & (1-\beta)G \le g < (1-\beta)(1+\beta)G \\ 0 & (1-\beta)(1+\beta)G \le g \le G \end{cases} \tag{4}$$

$$\Delta_3 = \begin{cases} 0 & 1 \le g < (1-\beta)G \\ 0 & (1-\beta)G \le g < (1-\beta)(1+\beta)G \\ 1 & (1-\beta)(1+\beta)G \le g \le G \end{cases} \tag{5}$$

In Formula (2), $Cauchy(0,1)$ is standard Cauchy distribution, $T(g)$ is T-distribution which considers the number of iteration g as degree of freedom parameter, and $N(0,1)$ is standard Gaussian distribution.

Definition 2.3. *(segmented mutation) The position of fruit fly individual* $Pos_i = (X_{i1}, X_{i2}, X_{i3}, \ldots, X_{id})$ *executes segmented mutation, see Formula (6) and Formula (7).*

$$Pos_i^M = (X_{i1} \times \Theta, X_{i2} \times \Theta, X_{i3} \times \Theta, \ldots, X_{id} \times \Theta) \tag{6}$$

$$\Theta = 1 + \varepsilon \times \xi \tag{7}$$

In Formula (6) and Formula (7), we add segmented mutation disturbance to optimization variable Pos_i of fruit fly individual (d is the dimension of the search space). On the basis of population history information, disturbance adjusting ability gradually decreases with the evolution of the segmented mutation effectiveness coefficient ε. Segmented mutation factor ξ combines Cauchy distribution, T-distribution and Gaussian distribution. Cauchy distribution has the strongest disturbance ability, and it is suitable for the early stage of the evolution. Gaussian distribution has the weakest disturbance ability, and it is suitable for the later stage of the evolution. The disturbance ability of T-distribution is between Cauchy distribution and Gaussian distribution, so it is suitable for the medium stage of the evolution. From above we can see that segmented mutation can avoid FOA easily trapping into local extremum and improve the precision and speed.

2.2. **Description of FOA-SM.** FOA-SM adopts segmented mutation that is mentioned by Section 2.1 to improve FOA, and then is put forward. Convergence speed of FOA is greatly enhanced on account of segmented mutation idea. The specific process of FOA-SM is as follows.

Step 1 Set the population size N, the maximum number of iteration G, and randomly initialize the fruit flies crowd position $Pos = (X_1, X_2, X_3, \ldots, X_d)$.

Step 2 Calculate the random direction and distance of fruit fly individual by using sense to search for food according to Formula (8). In Formula (8), L is scouting distance, X_{ij} is the jth dimension coordinate value of the ith fruit fly individual, and X_j is the jth dimension coordinate value of the fruit flies crowd.

$$X_{ij} = X_j + L \times rand() \quad j = 1, 2, 3, \ldots, d \tag{8}$$

Step 3 Calculate taste concentration determination value J_i of the ith fruit fly individual according to Formula (9).

$$J_i = \frac{1}{\sqrt{\sum_{j=1}^{d} X_{ij}^2}} \tag{9}$$

Step 4 Calculate taste concentration of the ith fruit fly individual according to Formula (10). $SCF()$ is taste concentration function, namely objective function, and $smell_i$ is the taste concentration value of the ith fruit fly individual.

$$smell_i = SCF(J_i) \tag{10}$$

Step 5 Find out the fruit fly individual with the best taste concentration among fruit flies crowd, and then $smell_{best} = smell_i$, $Pos_{best} = Pos_i$.

Step 6 Judge whether the values of $smell_{best}$ and Pos_{best} in Step 5 are better than the last generation, if meeting, turn to Step 7, else turn to Step 8.

Step 7 Reserve the current optimal value and optimal location according to Formula (11) and make the fruit flies crowd fly to the current best location, turn to Step 10.

$$Best_{smell} = smell_{best}, Pos = Pos_{best} \tag{11}$$

Step 8 Judge whether the optimal position of fruit fly remains unchanged or changes little in two consecutive iterations, if meeting, turn to Step 9, else turn to Step 10.

Step 9 Perform segmented mutation according to Formula (6) and Formula (7), turn to Step 10.

Step 10 Judge whether the iteration number reaches the maximum number of iteration, if meeting, terminate the algorithm, else turn to Step 2.

2.3. **Powell method.** Powell method is a modified coordinate rotation algorithm. The specific process of Powell method is as follows.

Step 1 Determine the axis direction and the initial point $x^{(0)}$.

Step 2 Alternately execute linear search along the axis direction, and get $x^{(i)}$, $i = 0, \ldots, n$.

Step 3 Consider $x^{(0)} := x^{(n)}$ as initial point, judge whether getting solution of the problem, if meeting, turn to Step 4, else turn to Step 1.

Step 4 Output solution of the problem.

3. Biomedical Image Registration Based on FOA-SM and Powell.

3.1. **Selection of the similarity measure.** In this paper we select mutual information as similarity measure. The mutual information calculation of two images I_X and I_Y is shown in Formula (12).

$$M(I_X, I_Y) = -\sum_{i_x} P_{I_X}(i_x) \log_2^{P_{I_X}^{(i_x)}} - \sum_{i_y} P_{I_Y}(i_y) \log_2^{P_{I_Y}^{(i_y)}} + \sum_{i_x, i_y} P_{I_X, I_Y}(i_x, i_y) \log_2^{P_{I_X, I_Y}^{(i_x, i_y)}} \tag{12}$$

In Formula (12), P_{I_X} is probability distribution function of image I_X, P_{I_Y} is probability distribution function of image I_Y, and P_{I_X,I_Y} is joint probability distribution function of images I_X and I_Y.

3.2. **The step of biomedical image registration.**

Step 1 Input the reference image I_X and the floating image I_Y.

Step 2 Define variables Ψ_X and Ψ_Y, $\Psi_X = I_X$, $\Psi_Y = I_Y$, turn to Step 3.

Step 3 Calculate the mutual information of Ψ_X and Ψ_Y according to Formula (12), judge whether the mutual information value is maximum, if meeting, turn to Step 6, else turn to Step 4.

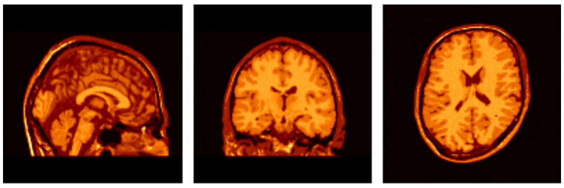
Step 4 Firstly, calculate optimized registration transformation parameter Ω_1 by using Powell. Secondly, consider Ω_1 as the center, and calculate another optimized registration transformation parameter Ω_2 by using FOA-SM. Thirdly, take the maximum value of Ω_1 and Ω_2 as the final optimized registration transformation parameter Ω.

Step 5 Floating image I_Y executes registration transform by using registration transformation parameter Ω, the floating image after registration transformation is I_Y^T, $\Psi_X = I_X$, $\Psi_Y = I_Y^T$, turn to Step 3.

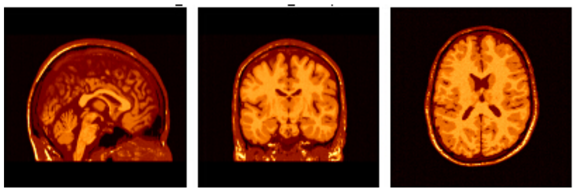
Step 6 Termination. Output the final floating image I_Y^T.

4. Simulation Results and Analyses.

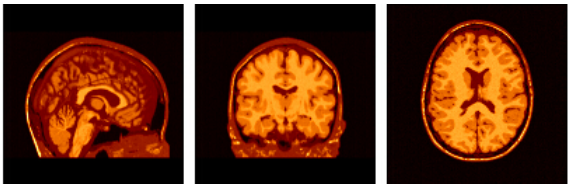
4.1. **The experimental data.** In this paper, the experimental data is from McGill university's McConnell brain MRI biomedical image library [12]. The extracted four groups of experimental data are shown in Figure 1. The parameters of the four groups of experimental data are shown in Table 1. The experimental parameters setting of FOA-SM is shown in Table 2.



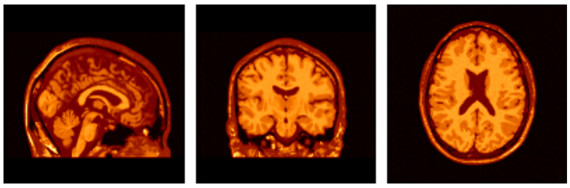
(a) The first group of MRI image



(b) The second group of MRI image



(c) The third group of MRI image



(d) The fourth group of MRI image

FIGURE 1. Four groups of brain MRI experimental data

TABLE 1. The parameters of the four groups of MRI experimental data

image	modality	slice thickness (mm)	noise rate	non-uniform level
the first group	T1	5	3%	20%
the second group	T2	3	1%	40%
the third group	T1	4	5%	20%
the fourth group	T2	3	3%	40%

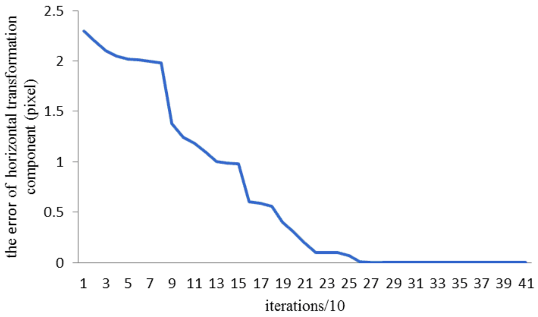
TABLE 2. The experimental parameters setting of FOA-SM

population size N	maximum number of iteration G	searching distance L	segmented variation parameter μ	segmented variation parameter α	segmented variation parameter β
30	1000	1	15	1.618	0.618

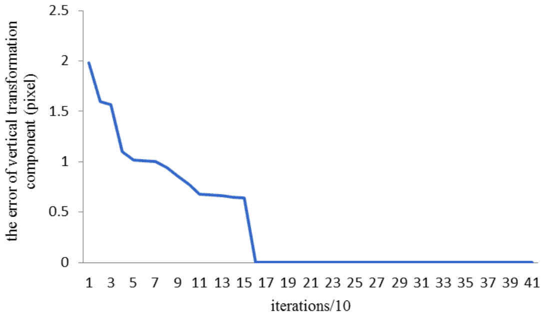
4.2. **The registration results analyses.** Registration transformation parameter is set as $\Omega = [x, y, \phi]$, x is horizontal transformation component, y is vertical transformation component, and ϕ is angle component for going around the origin. Figure 2 shows the transformation relations between the registration results and algorithm iterations. In Figure 2, Y-axis is the error of registration transformation component parameter, and X-axis is the number of iterations.

From Figure 2 we can see, the error of horizontal transformation component is approximately zero near 260 iterations by using our method. The error of vertical transformation component is approximately zero near 160 iterations by using our method. The error of angle component for going around the origin is approximately zero near 180 iterations by using our method. Three transformation components all can obtain approximately zero error, which illustrates that our method has higher accuracy, also because the maximum number of iterations is 1000, and three transformation components are fast convergence within 260 iterations, which illustrates that our method has faster registration speed.

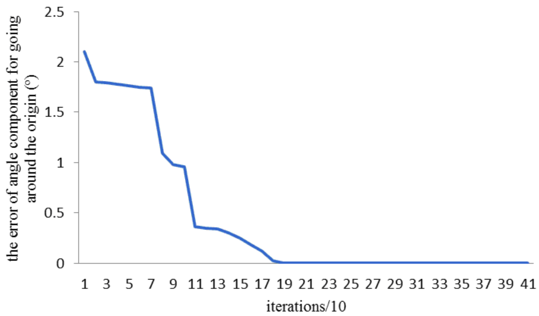
The comparison results of various registration methods are shown in Table 3. From Table 3 we can see: (1) The simple Powell algorithm does not combine with other algorithms, so it consumes less time, and the precision and accuracy of registration are far less than other methods; (2) Due to the fact that basic FOA is easy to fall into local extremum, basic FOA has slow convergence speed and low accuracy. Registration speed and accuracy of basic FOA combined with Powell are both lower than our method; (3) Using improved GA to optimize the registration process can overcome the problem of



(a) The error of horizontal transformation component



(b) The error of vertical transformation component



(c) The error of angle component for going around the origin

FIGURE 2. The relationship between the error of transformation parameter and the number of iterations

TABLE 3. The comparison of various registration methods

method	horizontal transformation component (pixel)	vertical transformation component (pixel)	angle component for going around the origin (°)	mutual information	time (s)
Powell	8.567 3	13.679 3	6.093 1	1.108 5	110.56
basic FOA combined with Powell	8.454 1	11.267 9	5.834 8	1.114 8	160.02
improved GA combined with Powell	2.784 9	6.994 6	4.898 6	1.120 8	156.98
our method	2.326 9	6.726 6	4.830 9	1.136 0	128.86

local minima, but later in the optimization process the convergence speed is slow. Registration speed and accuracy of improved GA combined with Powell are both lower than our method; (4) Our method can improve the accuracy of registration, effectively shorten the optimization time and has the higher registration precision and accuracy.

5. **Conclusions.** In this paper, we have combined Cauchy distribution, T-distribution and Gaussian distribution, and then proposed segmented mutation. The mutation ability of segmented mutation is dynamic adjusted through the efficiency coefficient ε. Due to the fact that FOA is easy to fall into local extremum, in this paper, we have used segmented mutation to improve FOA, and then FOA-SM is proposed. Using mutual information as the similarity measure, we have combined FOA-SM and Powell for biomedical image registration. Finally, a method based on FOA-SM and Powell for biomedical image registration is proposed. Simulation results show that our method runs faster, and has higher accuracy, so it is an effective method for automatic registration. In the following work, we

will expand our method into the high-dimensional space (such as four space dimensions) and improve the operation speed for application in clinical diagnosis.

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