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Social Spider Optimization Algorithm in Multimodal Medical Image Registration

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Abstract

Image registration is one of the most essential applications of image processing, especially in medical. The purpose of image registration is to find the optimal parameters of conversion functions. The selection of appropriate optimization algorithms is very important in determining the optimal parameter. The Social Spider Optimization (SSO) algorithm is one of the meta-heuristic methods that prevents premature convergence. In this paper, medical image registration technique is suggested based on the SSO algorithm. The simulation results on Brain Web dataset affirm the suggested method outperforms classical registration methods in terms of convergence rate, execution time.

1. Introduction

Image registration is one of the most important branches of computer vision that is used in identifying changes, image fusion, image mosaics, image analysis and so on[1, 2]. Image registration is the process of finding geometric conversions images, taken at different imaging conditions [3]. Image registration approaches can be generally divided into two categories, feature-based approaches and intensity-based approaches[4, 5]. Intensity -based approaches versus feature-based approaches do not require preprocessing such as segmentation [6, 7].

Intensity-based methods usually include three steps: search space, similarity criteria, and search strategy [8, 9]. In the search space stage, based on the type of images and the distortion between the images, a suitable conversion for alignment is selected. Rigid and non-rigid conversion are examples of conversions. Similarity criterion is an index that measures the degree of similarity (correspondence) between two images (fixed, moving) that mutual information, correlation coefficients, joint entropy and etc are examples of similarity criteria. Mutual information (MI) criterion is one of the most popular similarity criteria, which is very effective in matching multimodal images [10, 11]. The search strategy step is one of the most important steps in intensity-based methods because the performance of this step directly affects the matching results [12, 13].In this step, the parameters of the optimal conversion function are computed using the optimization algorithm for image alignment. Optimization algorithms can be broadly divided into local and global categories [9]. Local algorithms have high exploration power and these algorithms have less execution time. Local optimizers may find local optimizers instead of global optimizers, which is one of the disadvantages of these optimizers.

In [14], the simulated annealing algorithm is used for the noise image registration. In [15], genetic algorithm and mutual information similarity criterion are used to register the multimodal images of the brain. In [16], Genetic Algorithm (GA) and Affine conversion have used for image registration. In [6], the Particle Swarm Optimization (PSO) algorithm and the mutual information criterion have used in the medical multimodal image registration. In [17], the genetic algorithm and the simulated annealing algorithm are compared to retina image registration, which shows the genetic algorithm has better performance in terms of convergence rate and speed. In [18], grey-wolf-based Wang's demons algorithm is used for retinal images registration. In [7], the Bat algorithm and Grey Wolf optimization with the criterion of similarity of mutual information is used to register medical images such as brain and retina. In [19], the firefly algorithm with the correlation coefficient similarity metric is used for image registration. This algorithm has better accuracy and speed in image registration than PSO algorithm. In [20], the Accelerated Particle Swarm Optimization (APSO) algorithm with the criterion of similarity of mutual information for image registration is presented. This algorithm has a better speed but less accuracy in image registration than the firefly algorithm. In [21], artificial bee colony algorithm with mutual information similarity metric is proposed for image registration. This method is more accurate than other methods. In [22], PSO and the Artificial Bee Colony algorithm (ABC) are used in medical images registration. The results show that ABC algorithm is more accurate than PSO algorithm, but this algorithm has more execution time. In [8], ant colony algorithm and mutual information are presented in registration MRI and CT images of the brain. In [10], ant colony algorithm and Differential total variation (DTV) are proposed for search space and similarity metric in multimodal remote sensing images registration, respectively. In [23] , the PSO method and the sequential quadratic programming (SQP) method are combined in the search space, called the PSOSQP method. This method has better accuracy and speed in image registration than other methods such as GA, PSO and ABC. In [11], ant colony algorithms have been improved for image registration, which is of better quality and speed than other methods such as classic ant colony algorithm, PSO.

Choosing a suitable method for search strategy is very important because the speed of convergence, execution time and finally reaching the optimal answer depends on the type of search strategy. Various meta- heuristic algorithms have been used so far for search strategy in image registration. The social spider optimization algorithm is another meta-heuristic algorithm. This algorithm was presented by Erik Cuevas et al based on the cooperative characteristics of the social spider [24]. The social spider algorithm has been widely used in various applications such as image contrast enhancement [25], anti-islanding protection [26], text psychology analysis [27], and energy theft detection[28] .This algorithm unlike other algorithms as PSO [29], GA [30], Cuckoo Search (CS) [31], ABC [32], Harmony Search (HS) [33], and Social Network Optimization (SNO) [9], prevents premature convergence to local optimum solutions or a limited balance between exploration and exploitation [34]. These advantages motivate the use of the SSO for medical images registration. In this article, the SSO algorithm is proposed for finding the optimal parameters of affine conversion in medical image registration. Another innovation is the study of similarity criteria such as mutual information, normalization of mutual information (NMI), and Sum of Squared Differences (SSD) in the registration of brain images.

Organization of the remainder of the paper is as follows. In Section II, the suggested algorithms are presented and in Section III, the tests results are studied. Section IV and Section V, are discussion and conclusions are studied, respectively.

III- METHOD

The image registration consists to search for the optimal geometric conversion between moving image (s) and fixed image (r) according to (1).

$$T^* = \arg\max S(r, T_a(s)) \quad \textbf{(1)}$$

In (1), T_a is the transformation matrix by transformation parameters a, and S is fitness is maximized when the r image is completely aligned with $T_a(s)$ image.To register the transformed moving image $T_a(s)$ to the fixed image r, the set of parameters a that maximizes the fitness function S needs to be estimated by search strategy .The conversion function, similarity metric, and search strategy used are described below.

A. Affine Conversion Function

An appropriate conversion type should be selected for image registration according to the type of images and the deviation between the images. Conversions are broadly classified into two categories, rigid conversion and non-rigid conversion [7, 20]. The Affine conversion is one of the non-rigid transformations that includes four parameters, scaling (S), translation (T), rotation (R) and shear (SH) according to.(2).

$$AC = S \times T \times R \times SH$$

$$AC = \begin{bmatrix} S_1 & 0 & 0 \\ 0 & S_2 & 0 \\ 0 & 0 & 1 \end{bmatrix} \times \begin{bmatrix} 1 & 0 & t_x \\ 0 & 1 & t_y \\ 0 & 0 & 1 \end{bmatrix} \times$$

$$\begin{bmatrix} \cos(\theta) & -\sin(\theta) & 0 \\ \sin(\theta) & \cos(\theta) & 0 \\ 0 & 0 & 1 \end{bmatrix} \times \begin{bmatrix} 1 & sh_1 & 0 \\ sh_2 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{2}$$

B. Similarity Metric

The similarity metric measures the similarity between the fixed image and the moving image, which is used as a fitness function in image registration algorithms. Similarity metrics are mutual information, correlation, entropy, etc. The choice of appropriate similarity metric depends on the type of image [35]. In this paper, fitness functions such as mutual information according to (3) and normalized mutual information according to (4) and SSD according to (5) are used.

$$MI(A,B) = H(A) + H(B) - H(A,B) \tag{3}$$

$$NMI(A,B) = \frac{H(A)+H(B)}{H(A,B)} \tag{4}$$

$$SSD = \sum_{i=1}^{n} \left(A(z_i) - B(Tz_i)\right)^2 \tag{5}$$

In (3-5), $H(A,B)$ is the joint entropy, $H(A)$ and $H(B)$ are marginal entropy in the fixed image and marginal entropy in the moving image, respectively.

C. search strategy by SSO Algorithm

The social spider optimization algorithm was introduced in 2013 [24]. Social spider-seeking behavior can be described as the collective movement of spiders toward the food source. Every spider on the web has a position and fitness, which indicates the potential to find a food source in that position. The spider can move freely on the web but it cannot leave the web. When a spider moves to a new position, it produces a vibration that propagates across the web. The social members of the spider are divided into males and females, in which the number of females is more than males. The number of female spiders makes up about 90% of the population. The spider interacts with the vibration of the strings on the web. The vibration that a female spider receives is according to (6), depending on the size of the spider and the distance of the spiders, regardless of the type of spider.

$$Vib_{i,j} = w_j \cdot e^{-d_{i,j}^2} \tag{6}$$

In (6),is the $d_{i,j}$ is the weight of spider j and w_j Euclidian distance between spiders i and j.
Female spiders are generally able to sense three vibrations from spiders: 1- The closest spider with a higher weight (v_{ibci}), 2- The earliest spider in the community (v_{ibbi}),3-the closest male spider to the female spider (v_{ibfi}).
The female spider may have a gravitational or repulsive motion toward the source of the vibration. If the spider is attracted to the vibration, its position is updated according to (7), and if the spider moves away from the vibration position, its position is updated according to (8).

$$f_i^{k+1} = f_i^k + \alpha \cdot Vibc_i \cdot \left(s_c - f_i^k\right) + \beta \cdot Vibb_i \cdot \left(s_b - f_i^k\right) + \delta \cdot \left(rand - \frac{1}{2}\right) \tag{7}$$

$$f_i^{k+1} = f_i^k - \alpha \cdot Vibc_i \cdot \left(s_c - f_i^k\right) - \beta \cdot Vibb_i \cdot \left(s_b - f_i^k\right) + \delta \cdot \left(rand - \frac{1}{2}\right) \tag{8}$$

In (7-8), $\alpha, \beta, \delta,$ and $rand$ are random numbers betweenshows the iteration number. k and $[0,1]$, who have i are the closest members to the s_c, s_b the most weight and the best member in the whole population S , respectively.

Male spiders are divided into two groups, dominant spiders and recessive spiders, according to the biological behavior of social spiders. Dominant male spiders are heavier and female spiders are more likely to be attracted to its vibrations, but recessive male spiders tend to move toward the center of the population and use food resources wasted by the dominant spider as a strategy. The position of the dominant spider is updated according to (9) and the position of the defeated spider is updated according to (10).

$$m_i^{k+1} = m_i^k + \alpha \cdot V_{ibfi} \cdot \left(s_f - m_i^k\right) + \delta \cdot \left(rand - \frac{1}{2}\right) \quad (9)$$

$$m_i^{k+1} = m_i^k + \alpha \cdot \left(\frac{\sum_{h=1}^{N} m_h^k \cdot w_{Nf+h}}{\sum_{h=1}^{N} w_{Nf} + h} - m_i^k \right) \quad (10)$$

In (9-10), $\alpha, \beta,$ and $rand$ are random numbers between $[0,1]$ and s_f is the nearest female to male i whereas $\left(\frac{\sum_{h=1}^{N} m_h^k \cdot w_{Nf+h}}{\sum_{h=1}^{N} w_{Nf+h}} \right)$ is the weighted mean of the male population M.

II. IMPLEMENTATION AND EXAMINATION OF RESULTS

To evaluate the function of the suggested approach, three sets of tests are performed with the classical algorithms such as GA, PSO. The database used in this article contains images with different modalities such as a set of T1, T2 and PD-weighted MR images of size $256 \times 256 \times 32$ voxels from the BrainWeb database [36]. In the first set of experiments, the performance of the suggested approach on mono-modal images of the brain is investigated. In the second test set, the performance of the suggested approach on multi-modal brain of images is examined. In the third test set, effect of different Fitness functions in image registration is studied. The results of the tests are checked by convergence rate, execution time, and RMSE and average MI.

A.Registration performance of the suggested approach on mono-modal images

In the first test, the proposed algorithm is applied on mono-modal brain images, and its function is investigated (Fig.1 and Table1) .

TABLE I- Results of GA-SSD, PSO-SSD and SSO-SSD in mono-modal image registration

Type image	Algorithm	RMSE
T1-T1	GA-SSD	5.481
	PSO-SSD	4.965
	SSO-SSD	**3.387**
T2-T2	GA-SSD	6.142
	PSO-SSD	4.854
	SSO-SSD	**4.307**

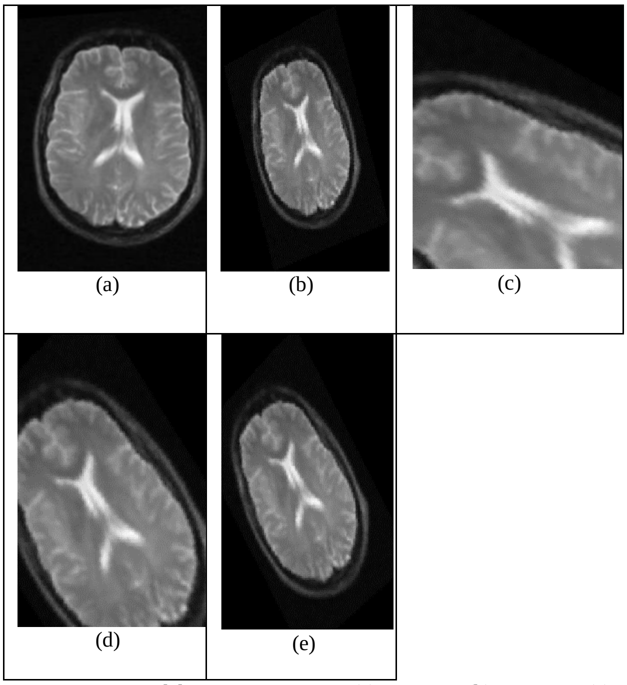
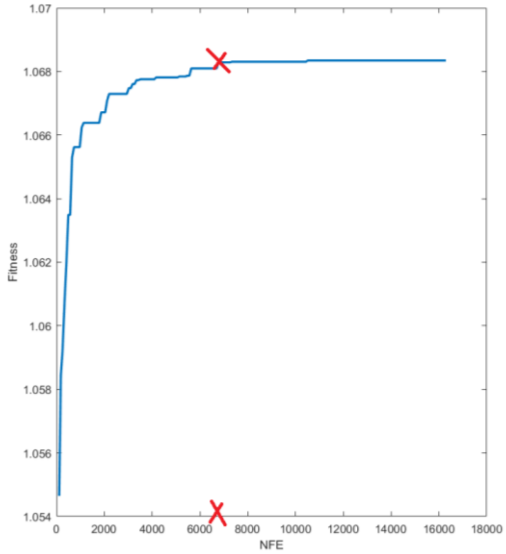


Fig.1. mono- modal image registration, (a)T2 image, (b) T2 image, (c) mono-modal image registration by GA, (d)mono-modal image registration by PSO (e) mono- modal image registration by SSO

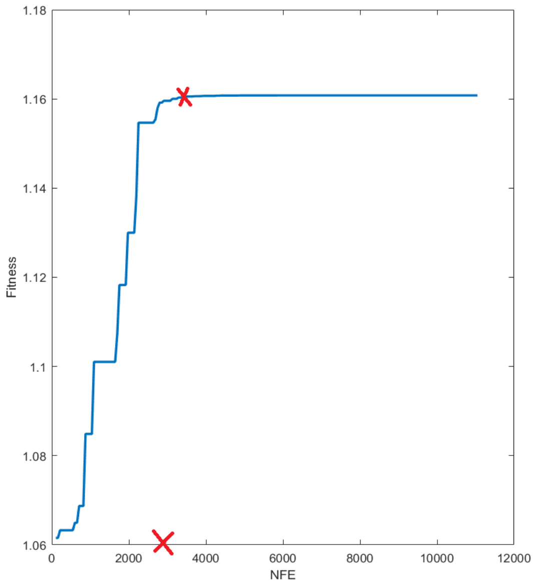
According to Fig.1, it can be concluded that the SSO has a better function in image registration than other meta-heuristic algorithms.

B. Registration performance of the suggested approach on multimodal images

In this test, the multimodal brain images were used to assess the functionality of the proposed method in registration process; the results are shown in Fig. 2 &3 and Table 2.



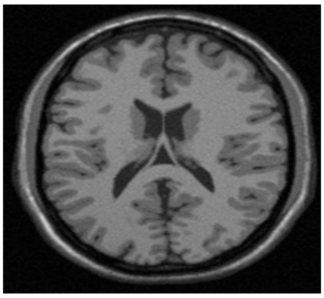
(a)



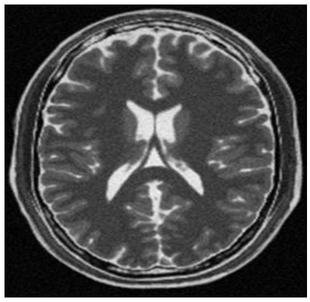
(b)

Fig.2. Graph of number functions evaluated in terms of fitness functions, (a) GA - MI, (b) SSO algorithm-MI

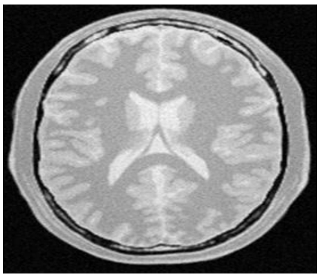
Fig.2 is a graph of the number of functions evaluated (NFE) in terms of the mutual information fitness function. To compare these two algorithms (GA, SSO), the same population size and number of iterations are considered. According to the graphs, it was found that the SSO algorithm has reached a better optimization value than the GA. On the other hand, the SSO algorithm is far more powerful than the GA in terms of convergence speed by comparing the NFE. For example, to optimize this problem, the number of evaluated functions for the GA is 7000 and for the social spider algorithm is 3500, which indicates that the GA results in image registration solving fewer equations than the GA. This demonstrates the effective efficiency of the SSO algorithm in brain images registration.



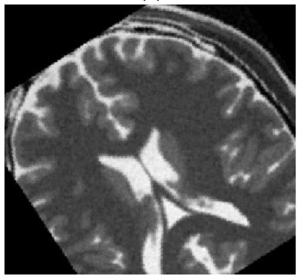
(a)



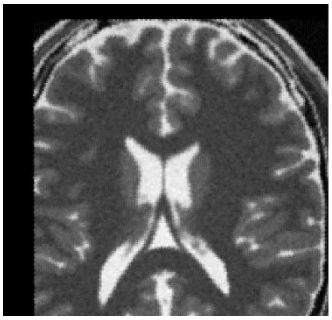
(b)



(c)

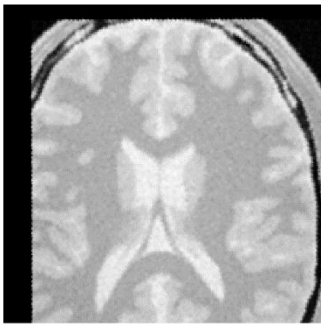


(d)



(e)

(f)



(g)

Fig.3. image registration, (a)T1 image, (b)T2image, (c) PD image (d) image (T1&T2) registration by GA, (e) image (T1&T2) registration by SSO, (f) image(T2&PD) registration by GA (g) image(T2&PD) registration by SSO

The unsuccessful registration of the GA is due to not finding the optimal cconversion parameters (Fig.3, d). In the proposed methods, due to finding the most optimal conversion parameters, the registration process is better done (Fig.3 e.g.).

TABLE II-MAE comparison between genetic-MI, PSO-MI, and SSO-MI

Image	GA -MI				PSO-MI				Proposed SSO-MI			
	t_x	t_y	θ	times	t_x	t_y	θ	times	t_x	t_y	θ	times
T1-T2	0.303	0.247	0.0026	418.33	0.301	0.228	0.0023	341.17	0.272	0.225	0.0019	294.44
T2-PD	0.383	0.296	0.0025	513.28	0.306	0.224	0.0022	427.20	0.295	0.217	0.002	350.55
Average	0.343	0.271	0.0025	465.80	0.3035	0.226	0.0024	384.19	**0.2835**	**0.221**	**0.00195**	**322.50**

C. The effect of different Fitness functions in image registration

In this test, five pairs of multimodal images and five pairs of mono modal images were used to evaluate different fitness function (Table 2).

Table II-Evaluate image registration based on SSO algorithm using different fitness functions

Type image	Algorithm	Average-MI
Mono modal	SSO-MI	1. 120
	SSO-NMI	1.191
	SSO- SSD	**1.138**
Multi modal	SSO-MI	**1.16**
	SSO-NMI	1.141
	SSO-SSD	1.119

III. **Discussion**

In this part, registration results of the suggested method and GA, and PSO algorithms in the brain database for all evaluation criteria will be reviewed.

The image registration performance according to the RMSE from best to worst is the SSO, PSO, and the genetic algorithm, respectively (Table I). Table II shows the median absolute error (MAE) value for each Affine conversion parameter in each algorithm that parameter t_x, the order of algorithm performance from best to worst is SSO (0.2835), PSO (0.3035) and GA (0.343). For parameter t_y, and θ the order of algorithm from best to worst is SSO (0.221, 0.00195), PSO (0.226, 0.0024) and GA(0.271, 0.0025), respectively. We can conclude that the SSO performs best for the estimation of all parameters. The SSO algorithm has the highest speed and the GA has the lowest speed in medical images registration (Table II). In Table III, different fitness functions for mono-modal and multimodal images registration were investigated. The mutual -information fitness function for multimodal image registration and the SSD fitness function for mono-modal images registration performed better.

IV. **Conclusion**

In this article, SSO-based image registration is proposed using similarity metrics such as MI, NMI, and SSD. First, the performance of these similarity metrics is compared with each other, and then the performance of the SSO is compared with other optimization algorithms such as GA and PSO in brain image registration. The results show that the metric similarity of mutual information has a better performance in multimodal images registration and the function of SSO is better in terms of speed and quality of image registration than GA and PSO algorithm. We will try to use this suggested approach in other image registration such as remote-sensing image and natural image in future works.

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references

[1] Z. Hossein-Nejad and M. Nasri, "Adaptive RANSAC and extended region-growing algorithm for object recognition over remote-sensing images," Multimedia Tools and Applications, 2022.

[2] Z. Hossein-Nejad and M. Nasri, "Clustered redundant keypoint elimination method for image mosaicing using a new Gaussian-weighted blending algorithm," The Visual Computer, 2021/07/19 2021.

[3] Z. hossein-nejad and M. Nasri, "Clustered Redundant Keypoint Elimination SURF method in MRI Image Registration based on Alpha-Trimmed Relationship," Frontiers in Biomedical Technologies, 2022.

[4] Z. Hossein-Nejad and M. Nasri, "Image Registration Based on Redundant Keypoint Elimination SARSIFT Algorithm and MROGH Descriptor," in 2022 International Conference on Machine Vision and Image Processing (MVIP), 2022, pp. 1-5.

[5] Z. Hossein-Nejad and M. Nasri, "Retinal Image Registration based on Auto-Adaptive SIFT and

Redundant Keypoint Elimination Method," in 2019 27th Iranian Conference on Electrical Engineering (ICEE), 2019, pp. 1294-1297.

[6] L. Rundo, A. Tangherloni, C. Militello, M. C. Gilardi, and G. Mauri, "Multimodal medical image registration using particle swarm optimization: a review," in 2016 IEEE Symposium Series on Computational Intelligence (SSCI), 2016, pp. 1-8.

[7] K. Shaw, P. Pandey, S. Das, D. Ghosh, P. Malakar, and S. Dhabal, "Image Registration using Bio-inspired Algorithms," in 2020 IEEE 1st International Conference for Convergence in Engineering (ICCE), 2020, pp. 330-334.

[8] H. Rezaei, M. Shakeri, S. Azadi, and K. Jaferzade, "Multimodality image registration utilizing ant colony algorithm," in 2009 Second International Conference on Machine Vision, 2009, pp. 49-53.

[9] M. P. Wachowiak, R. Smolíková, Y. Zheng, J. M. Zurada, and A. S. Elmaghraby, "An approach to multimodal biomedical image registration utilizing particle swarm optimization," IEEE Transactions on evolutionary computation, vol. 8, pp. 289-301, 2004.

[10] Y. Wu, W. Ma, Q. Miao, and S. Wang, "Multimodal continuous ant colony optimization for multisensor remote sensing image registration with local search," Swarm and Evolutionary Computation, vol. 47, pp. 89-95, 2019.

[11] Y. Tian and H. D. Ma, "Image registration based on improved ant colony algorithm," in Advanced Materials Research, 2013, pp. 683-686.

[12] Y. Zhuang, K. Gao, X. Miu, L. Han, and X. Gong, "Infrared and visual image registration based on mutual information with a combined particle swarm optimization–Powell search algorithm," Optik, vol. 127, pp. 188-191, 2016.

[13] H. Ghorbani and A. A. Beheshti, "Multiresolution registration of multitemporal remote sensing images by optimization of mutual information using a simulated annealing based Marquardt-Levenberg technique," in 2007 International Conference on Intelligent and Advanced Systems, 2007, pp. 685-690.

[14] I. Maglogiannis and E. Zafiropoulos, "Automated medical image registration using the simulated annealing algorithm," in Hellenic Conference on Artificial Intelligence, 2004, pp. 456-465.

[15] H. Zhang, X. Zhou, J. Sun, and J. Zhang, "A novel medical image registration method based on mutual information and genetic algorithm," in International Conference on Computer Graphics, Imaging and Visualization (CGIV'05), 2005, pp. 221-226.

[16] R. Suganya and S. Rajaram, "Mutual information and genetic algorithm based registration of MRI brain images," Canadian Journal on Biomedical Engineering and Technology, vol. 2, pp. 14-17, 2011.

[17] G. K. Matsopoulos, N. A. Mouravliansky, K. K. Delibasis, and K. S. Nikita, "Automatic retinal image registration scheme using global optimization techniques," IEEE Transactions on Information Technology in Biomedicine, vol. 3, pp. 47-60, 1999.

[18] S. Chakraborty, R. Pradhan, A. S Ashour, L. Moraru, and N. Dey, "Grey-Wolf-Based Wang's Demons for retinal image registration," Entropy, vol. 22, p. 659, 2020.

[19] S. Chakraborty, N. Dey, S. Samanta, A. S. Ashour, and V. E. Balas, "Firefly algorithm for optimized nonrigid demons registration," in Bio-inspired computation and applications in image processing, ed: Elsevier, 2016, pp. 221-237.

[20] C.-L. Cocianu and A. Stan, "New evolutionary-based techniques for image registration," Applied Sciences, vol. 9, p. 176, 2019.

[21] Y. Qin, H. Hu, Y. Shi, Y. Liu, and H. Gao, "An artificial bee colony algorithm hybrid with differential evolution for multi-temporal image registration," in 2016 35th Chinese Control Conference (CCC), 2016, pp. 2734-2739.

[22] D. Sarvamangala and R. V. Kulkarni, "Swarm intelligence algorithms for medical image registration: A comparative study," in International Conference on Computational Intelligence, Communications, and Business Analytics, 2017, pp. 451-465.

[23] Y. Zhang and L. Wu, "Rigid image registration by PSOSQP algorithm," Advances in Digital Multimedia, vol. 1, pp. 4-8, 2012.

[24] E. Cuevas, M. Cienfuegos, D. Zaldívar, and M. Pérez-Cisneros, "A swarm optimization algorithm inspired in the behavior of the social-spider," Expert Systems with Applications, vol. 40, pp. 6374-6384, 2013.

[25] L. Maurya, P. K. Mahapatra, and A. Kumar, "A social spider optimized image fusion approach for contrast enhancement and brightness preservation," Applied Soft Computing, vol. 52, pp. 575-592, 2017.

[26] R. Vijay and V. Priya, "Anti-islanding protection of distributed generation based on social spider optimization technique," International Journal of Advanced Engineering Research and Science, vol. 4, p. 237193, 2017.

[27] A. Hosseinalipour, F. S. Gharehchopogh, M. Masdari, and A. Khademi, "Toward text psychology analysis using social spider optimization algorithm," Concurrency and Computation: Practice and Experience, vol. 33, p. e6325, 2021.

[28] D. R. Pereira, M. A. Pazoti, L. A. Pereira, D. Rodrigues, C. O. Ramos, A. N. Souza, et al., "Social-Spider Optimization-based Support Vector Machines applied for energy theft

detection," Computers & Electrical Engineering, vol. 49, pp. 25-38, 2016.
[29] J. Kennedy and R. Eberhart, "Particle swarm optimization," in Proceedings of ICNN'95-international conference on neural networks, 1995, pp. 1942-1948.
[30] M. Kumar, M. Husain, N. Upreti, and D. Gupta, "Genetic algorithm: Review and application," Available at SSRN 3529843, 2010.
[31] A. H. Gandomi, X.-S. Yang, and A. H. Alavi, "Cuckoo search algorithm: a metaheuristic approach to solve structural optimization problems," Engineering with computers, vol. 29, pp. 17-35, 2013.
[32] D. Karaboga and B. Basturk, "A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm," Journal of global optimization, vol. 39, pp. 459-471, 2007.
[33] X.-S. Yang, "Harmony search as a metaheuristic algorithm," in Music-inspired harmony search algorithm, ed: Springer, 2009, pp. 1-14.
[34] A. Luque-Chang, E. Cuevas, F. Fausto, D. Zaldivar, and M. Pérez, "Social spider optimization algorithm: modifications, applications, and perspectives," Mathematical Problems in Engineering, vol. 2018, 2018.
[35] R. Panda, S. Agrawal, M. Sahoo, and R. Nayak, "A novel evolutionary rigid body docking algorithm for medical image registration," Swarm and Evolutionary Computation, vol. 33, pp. 108-118, 2017.
[36] R.-S. Kwan, A. C. Evans, and G. B. Pike, "MRI simulation-based evaluation of image-processing and classification methods," IEEE transactions on medical imaging, vol. 18, pp. 1085-1097, 1999.