An improvised coral reef optimization-based image registration using modified mutual information method

Minu Samantaray[1], Millee Panigrahi[2], Krishna Chandra Patra[3]
[1]Department of Electronics, Sambalpur University Institute of Information Technology, Sambalpur, India
[2]Department of Electronics and Telecommunication Engineering, Trident Academy of Technology, Bhubaneswar, India
[3]Department of Electronics, Sambalpur University, Sambalpur, India

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ABSTRACT

Computer visualisation and medical applications require image registration. It includes transforming collective picture data into the familiar coordinate scheme. Metaheuristic-based methods were developed to explain the issue and improve the efficiency and accuracy of conventional image registration techniques due to their limitations. We describe a hybrid medical image registration technique using bio-inspired meta-heuristic algorithms: Better-offspring and multi-crossover strategies increase convergent time and solution quality with an improvised coral reef optimization with modified mutual information (ICOR-MMI) algorithm. This new optimization method (ICOR-MMI) proposes that coral reefs expand, compete for space, and reproduce. A linear weighted sum of image intensity and contour flow model intensity is added to the mutual information calculation. Including statistical and spatial image data improves image registration. The established technique has been tested and verified using multiple medical image data sets, some of which contain single-modality and mixed-modality images (CT, MRI). The registration validates the proposed model's accuracy and efficiency and shows posture's contribution by incorporating statistical and geographical image data. This strategy is adapted to the real-coding problem and tested for real-time issues. The ICOR-MMI algorithm-based hybrid approach outperforms current results in time efficiency and toughness.

Corresponding Author:

Minu Samantaray
Department of Electronics, Sambalpur University Institute of Information Technology
Odisha, India
Email: minu1485@gmail.com

1. INTRODUCTION

Clinical imaging relies heavily on image registration because it enables the consolidation of disparate pictures into a single representation (i.e., a common reference framework) from which physicians can draw more precise and timely diagnoses [1]. Image registration (IR) is the process of identifying the best mathematical transformation that accounts for the typical portion of the images [2]. Intensity-based methods and feature-based methods are the two main categories into which Registration techniques fall [3]. In feature-based registration process, some features such as points of control, edges, and curves, are recognized or extracted. In area (intensity) based approaches the registration is done directly with the raw pixel values.

There are typically three stages to a successful image registration: features can be selected and extracted in first step [4]. Secondly, methods for choosing the similarity metrics that will be used to compare the images and establish a match quality. The similarity metrics that evaluate the accuracy of a pair of images' matches are calculated by calculating the ratio of the images' intensity-based cost functions. Third, a spatial transformation model is defined to identify where in each image the same points are located.

Along with gathering input and output data, the research presented in this paper also includes two stages. In the first stage, images are filtered, features are extracted, and the similarity between the original and final images are measured with the help of the transformation model. In the second phase, an optimization technique is used to zero in on the best values or the transformation parameters.

The similarity measures are the most crucial part of the registration issue [5], [6]. Normalized cross correlation (NCC), mutual information (MI), sum of absolute differences (SAD), sum of squared intensity differences (SSD) are all measures used to measure degrees of similarity. Mutual information (MI)-based registration approaches [7] have shown great success in medical image registration, they solely take into account statistical information and completely ignore spatial information. The best transformation parameters needed for image alignment can be obtained by the application of optimization methods [8], [9].

The proposed ICOR method is appropriate for dealing with complicated optimization problems since it copies these cycles while leaning toward a firm compromise between diversity and explicitness. In order to prove the viability of our proposal, we encourage a careful trial arrangement comparing ICOR to state-of-the-art IR techniques. Each problem scenario is built using subsets of images from the widely used Brain Web dataset.

The significance of the results is evaluated using various factual tests. Briefly, this study makes the following contributions:

- A novel hybrid method for producing a highly matched image, based on improvised coral reef optimization with modified mutual information (ICOR-MMI).
- Improved registration efficiency is achieved by using a modified Contour flow model in the Mutual Information computation.
- Integrating spatial and statistical image data to enhance the exactness of registration method.
- Showcase proposed method's potential for registering multimodal medical images.

2. LITERATURE REVIEW

In the context of the planned work, this section summarizes the general state of research: Suganya *et al*. [10] suggested an automatic based intensity registration method of computer-based head image. The result yields good accuracy and quick processing time. Valsecchi *et al*. [11] proposed an integrated boundary mechanism of dynamic and restart intensity-based registration method within multiple resolution analysis. Bermejo *et al*. [12] introduced a bacterial foraging optimization algorithm (BFOA), intensity-feature based medical image registration obtained promising results in many real-world applications. Moslehi and Haeri [13] suggested a hybrid approach-based particle swarm optimization (HPSO) algorithm that conceptualizes two things of genetic algorithms namely crossover and subpopulation. The algorithm gives better results in terms of accuracy than previous applied genetic algorithm and particle swarm optimization (PSO). Tsai and Lin [14] address the defect detection application using fast-normalized cross correlation approach. Image mean, variance and cross-correlation are calculated for determining invariant of the image to the size of window of template. Samantaray *et al*. [15] proposed a method that is a combination of PSO and reformed mutual information (MI) as a similarity metric. The output yields accurate and effective registration results. Bhavana and Krishnappa [16] proposed a standard statistic based theoretical measure. It has shown probability theory concept where the correlation ratio of rigid images in multimodal registration gives a better robustness and accuracy trade-off. Yan *et al*. [17] tested chemical reaction optimisation (CRO) algorithm with various discrete and continuous several continuous and discrete specified problems in real world application scenarios and the result gives better performance.

3. PROPOSED METHOD

In this method, a hybrid technique is suggested that makes use of an ICOR-MMI as a measure of similarity metric. In order to combine statistical and spatial information, spatial information of the image is added to the mutual information result by combining the intensity of image with contour flow intensity. The performance metric is then obtained by maximizing the ICOR-MMI. Figure 1 illustrates the suggested model's registration process.

3.1. Image input and image normalization

Two-dimensional (2D) matrices are used to represent the inputs, and each matrix corresponds to a biomedical image that requires registration. Modifying both images first followed by normalizing the data to have all matrices' entries range from 0 to 1. The size, number of slices, and pixel spacing of multi-modal images can vary. Size of the image is standardized and noise is reduced for registration in step 1.

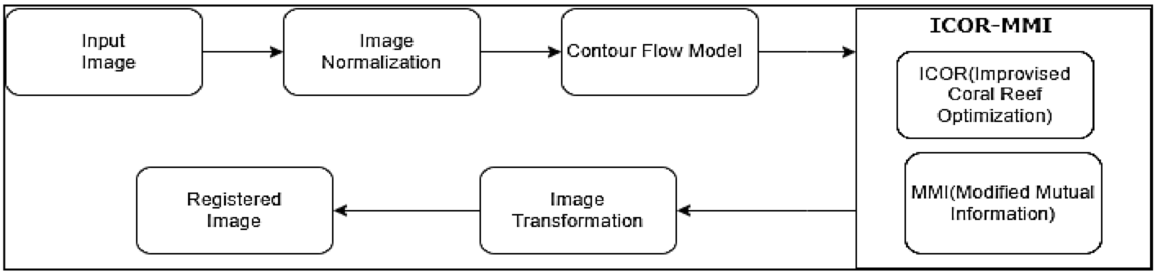


Figure 1. Block diagram of proposed model

3.2. Develop a contour model

With the goal of increasing the capture range of active contours, the contour flow model was developed [18]. This model is computed as a diffusion of the gradient vectors generated by the image. An "active contour" [19] is a curve drawn in the image domain that can be manipulated by both the internal forces generated by the curve and the external forces estimated from the image data to yield a minimized energy function stated in terms of the curve's position and orientation given in (1):

$$E = \iint \mu|\nabla V|^2 + |\nabla f|^2|V - \nabla f|^2 dxdy \quad (1)$$

where, $|\nabla V|^2 = (u^2x + v^2x + u^2y + +v^2y)$. V=Vector field
μ=parameter, which controls how the first and second terms in the integrand are traded off. The linear combination of the original intensity and the contour flow is used to incorporate spatial information into the calculation of mutual information MI.

3.3. Computation of modified mutual information (MMI)

Image intensity and the contour flow model are factors in modified MI. Modified MI depend on images intensity and contour flow model intensity. The new intensity is defined as a linear combination of I (x, y) the original intensity and $I_f(x, y)$ contour flow expressed in (2):

$$I_n = \beta I_f(x,y) + (1-\beta)I(x,y) \quad (2)$$

where β defines the tradeoff between $I(x, y)$ $andI_f(x, y)$.$I_f(x, y)$ is result of the vector field V obtained by solving (1) and given in (3):

$$I_f(x,y) = (u^2 + v^2)^{1/2} \quad (3)$$

the original intensity and the intensity of the contour flow are now combined to form new intensity matrices. Calculating mutual information with (4).

$$MI(I_{A,}I_B) = \sum_{a\in I_A}\sum_{b\in I_B} P_{AB}\,(a,b) log\,\frac{P_{AB}(a,b)}{P_A(a)P_B(b)} \quad (4)$$

Here $P_{AB}$is common probability &$P_A(a)$ $andP_B$ (b) are marginal discrete probabilities of intensity values of images. Using the histogram of an image, one may calculate the probability distribution of the image's grayscale values. A histogram of image is a graph that shows pixels quantity corresponds to each intensity value. By dividing each histogram item by the total number of entries, it is possible to estimate the joint probability distribution of the grey values in two images. The histogram of the original image and the rotated image are displayed in Figure 2. Each grey level is shown as a pin, indicating how many times it appears in the image. The entropies of two distinct images are a part of mutual information (MI). Step 5 demonstrates how to compute the modified mutual information (MMI) for transformation such as rotation, translation, and scaling to provide an optimal transformation matrix.

3.4. The optimization process

Any image registration approach must include the optimization system. It includes an iterative process that is responsible for examining the area of mathematical change under the control of the comparability metric. There are two accessible systems. Boundary-based techniques treat the registration as a continuous optimization problem hence the search is carried out simply in the space of the change boundaries. The most well-known examples of mathematical optimization algorithms include the angle plunge, constructed slope plummet, newton's and semi-newton strategies, Powell's methodology, and discrete optimization [15], [16]. It is very common to use strategies based on developing calculations and other metaheuristic (MH)s to mitigate the drawbacks caused by conventional search techniques [17]–[19]. In contrast, the search might be focused on the space of component correspondences in matching-based techniques. Either by considering similar parts (highlight-based tactics) or by contrasting a section of the image, the correlation should be achievable (force-based techniques). Through the use of least-squares analysis or other model fitting techniques, the boundaries of the change can be distinguished from the assessed matching [20]. The iterative closest point algorithm is a well-known matching-based algorithm [21].

Figure 2 represents the coral reef optimization output considering the parameter initialization taking no of generations as 500 and the number of opportunities for a new coral to settle in the reef is 3. The mean fitness and the best fitness has been plotted in the figure below showing best fitness value to be 97 and mean fitness to be 95.

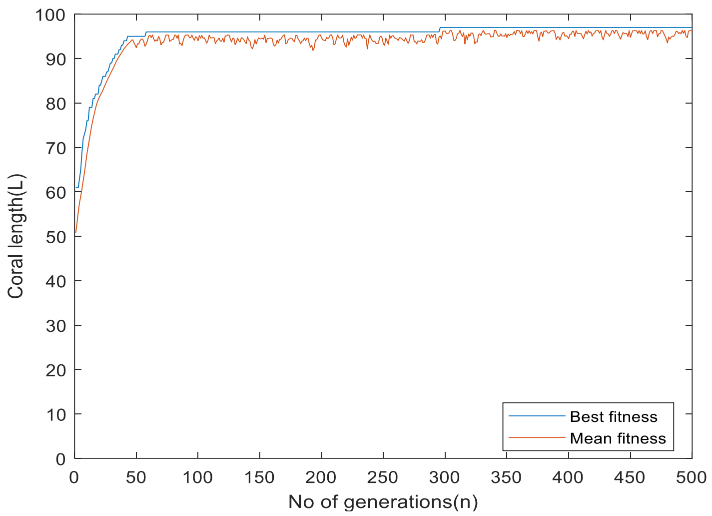


Figure 2. Coral reef optimization output

3.5. Optimum transformation

The test image (A) is registered with the target image (B) in the registration process through the application of a spatial transformation in the form of (5). For the purpose of representing the best spatial transform Ts, several transformation parameters are produced through optimization.

$$T_s = maxMI[A, T[B]] \tag{5}$$

Transformation Matrix is given by-(6):

$$T=\begin{bmatrix} scos\theta & -ssin\theta & t_x \\ ssin\theta & scos\theta & t_y \\ 0 & 0 & 1 \end{bmatrix} \tag{6}$$

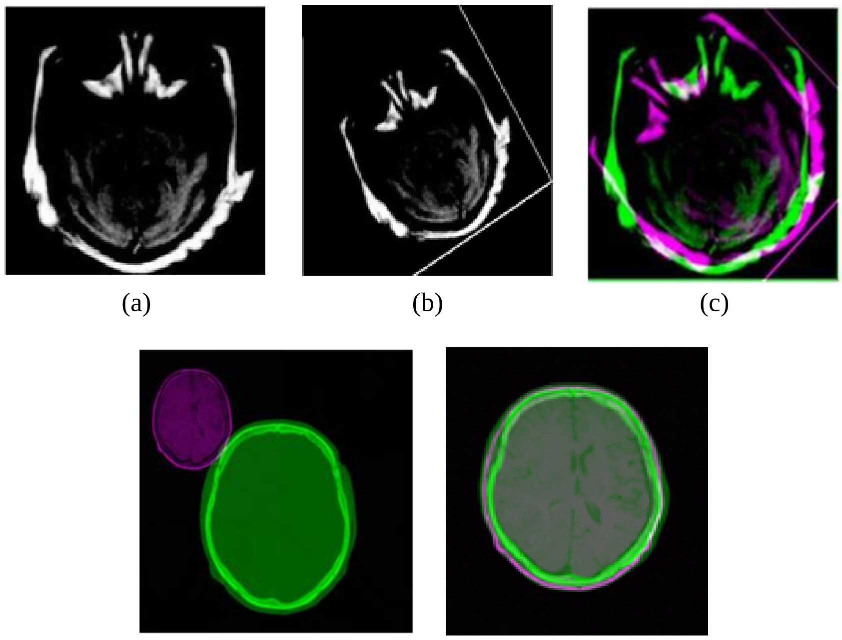
where, MI –Similarity measure between the images;
s - Scaling$t_x and t_y$ -Translation along x and y direction,
θ - Rotation parameter.

4. RESULTS AND DISCUSSION

The chosen medical databases are online datasets that stand out for their accessibility and dependability [22]. To verify the effectiveness of the registration procedure for creating a distorted image of the original, it is rotated and translated as illustrated in Figure 3. Figure 3(a) represents Monomodal MRI image before registration, Figure 3(b) depicts the MRI image with 45^0 rotation, and Figure 3(c) represents registered image. Figure 3(d) and Figure 3(e) show the outcomes of a multimodal brain image registration [23], where image - 1(magenta) is an MRI scanned image and image 2(green) is a CT scanned image.

All the tested images are grey level, and the considerable amount of distortion between the source and the target images makes for a challenging registration case. The proposed work is simulated in MATLAB 2020 and executed on a 2.27 GHz INTEL Core i5 (10^{th} generation) processor with 8 GB RAM.

In Figures 3(d)-3(e) the gray areas correspond to areas that have similar intensities that are overlapped, while green and magenta portion indicate the areas showing the variation in the intensity levels between the images. After registration it is seen that the misregistration in the volume of imageis along the axial slice at the locus of each plane. It is inferred from the fusion of CT and MRI image of brain through registration that the spatial information like pixel intensity are different for different images.



(a) (b) (c)

(d) (e)

Figure 3. Monomodal image registration (a) before registration, (b) MRI image 45^0 rotation, (c) after registrationand multimodal CT and MRI image registration, (d) before registration, and (e) after registration

By calculating the root mean squared error (RMSE) [24], Table 1 compares the matched (registered) image to the original image to determine how comparable they are in terms of translation, scaling, and rotation. These results show that the error is less than one unit. Table 2 compares the modified mutual information, which was previously stated in (3), to the regular mutual information using various transformation factors. Modified MI is seen to provide decreased RMSE in every possible case.

Table 1. Similarity measure parameters for evaluation of registered image

	Monomodal					Multimodal				
Transformation parameter	Before registration		After registration		Rmse	Before registration		After registration		Rmse
Translation	t_x	96	t_x'	97.32	0.58	t_x	96	t_x'	98.42	0.58
	t_y	88	t_y'	89.1	0.82	t_y	88	t_y'	89.23	0.82
Rotation	θ	45	θ'	44.8	0.00	θ	0	θ'	0	0.00
Scaling	s	3	s'	3.1	0.1	s	3	s'	3.2	0.1

Table 2. Comparison of RMSE in MI and modified mutual information

Transformation Parameter	Original Image		Mutual information (MI)	RMSE	Modified mutual information (MMI)	RMSE
Translation	t_x	96	98.2	1.63	97.6	0.8
	t_y	88	90.3		89.6	
Rotation	ϴ	0	0		0	
Scaling	s	3	3.32		3.09	

The performance metrics employed include the peak signal to noise ratio (PSNR), mutual information (MI), NCC and mean square error (MSE).

$$PSNR = 20log_{10} \frac{R^2}{MSE} \quad (7)$$

$$MSE = \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} [A(m,n) - B(m,n)]^2 \quad (8)$$

$$NCC = \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} \frac{X_{ij}Y_{ij}}{X^2{}_{ij}} \quad (9)$$

The genetic algorithm (GA) [25], PSO, firework algorithm (FA), and our suggested model are compared in additional trials. Table 3 demonstrates that using ICOR-MMI outperforms other conventional models. That indicates that the features of the image are improved following registration. The graphical representation given in Figure 4 provides the evidence of performance evaluation of the proposed model compared with the conventional methods in terms of MMI.

Table 3. Comparison of the proposed model with conventional methods

Algorithm	Parameters			
	MSE	PSNR	NCC	MMI
Genetic algorithm	66.6	29.95	0.87	8.25
PSO	87.4	28.99	0.91	9.23
Firework algorithm (FA)	88.2	27.43	0.75	7.45
Proposed model (ICOR-MMI)	48.8	19.4	0.94	9.92

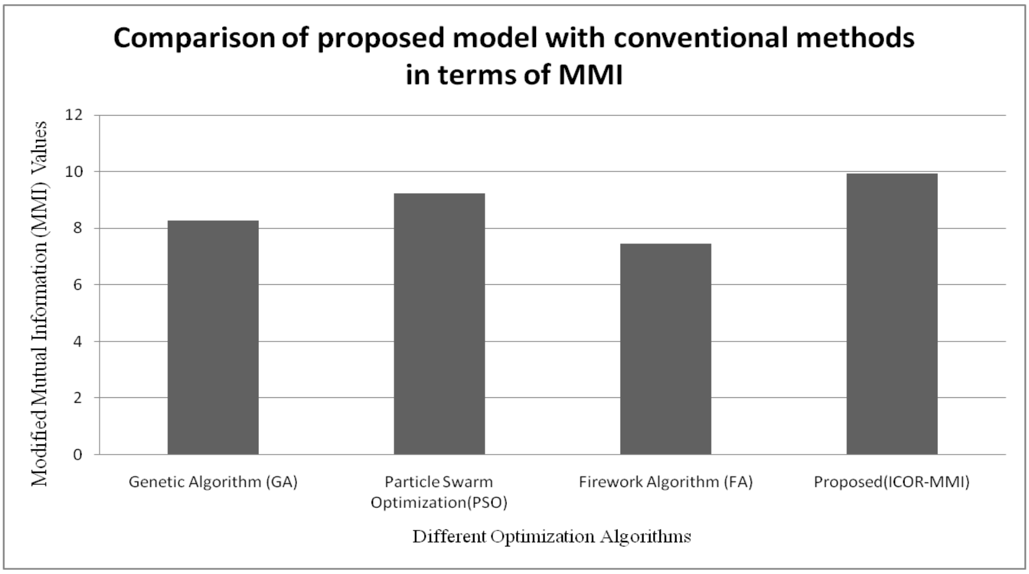


Figure 4. Comparison of proposed model with conventional methods in terms of MMI

5. CONCLUSION

As part of our research, we create a hybrid approach to image registration in the medical field. This technique uses a combination of the ICOR-MMI. The acquired registration findings show that geographical (contour flow) and statistical (MI) information were used, which leads to more precise registration results.

Different types of medical image data from different modalities have been used to successfully test the method (CT, MRI). This research shows that the ICOR-MMI method work well together to streamline the registration procedure. The ICOR optimization algorithm shows that the best fit and the mean fit gives approximately similar values of 97 and 95 respectively in accordance to the coral length. The data collected during registration demonstrates the robustness, precision, and effectiveness of the proposed approach.

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BIOGRAPHIES OF AUTHORS

Minu Samantaray has completed her Bachelor in Electronics and Telecommunication Engg. and Master in Electronics and Telecommunication Engineering from BPUT Odisha, India. Presently she is working as Assistant Professor in Dept of Electronics and Telecomm Engg. at Trident Academy of Technology, Bhubaneswar, Odisha, India. She has 15 years of teaching experience and published more than 7 research papers in journal and conferences. Her area of research interest is machine learning and deep learning and guided numerous B.Tech Projects. She is a lifetime member of ISTE and IETE. She can be contacted at email: minu1485@gmail.com.

Dr. Millee Panigrahi has completed her Bachelor in Electronics and Telecommunication Engg. and Master in Signal Processing and Telematics from BPUT, Odisha, India. She has been awarded with Ph.D. from Sambalpur University. Presently she is working as Associate Professor in Dept of Electronics and Telecomm Engg. at Trident Academy of Technology, Bhubaneswar, Odisha, India. She has 14 years of teaching experience and published more than 12 research papers in International Journals and conferences. Her area of research interest is biomedical signal processing, machine learning and Embedded system and guided numerous B.Tech Projects. She is a lifetime member of ISTE and ISSS. She is an active reviewer in SCI indexed journals and scopus journals. She can be contacted at email: millee.panigrahi82@gmail.com.

Dr. Krishna Chandra Patra has completed his Ph.D. in Electronics from Delhi University. Presently he is working in Department of Electronics in Sambalpur University, Odisha, India. He has published more than 20 papers in SCI and Scopus indexed journals and conferences. More than 10 candidates have completed their M.Phil/M.Tech under his supervision in the area of Electronics Communication System and related disciplines. Under his supervision 6 Ph.D. scholars have been awarded in different fields of research. His area of research is signal processing, image processing, optical communication techniques and on photonics. He can be contacted at email: krishnach.patra@gmail.com.