Satellite Image Registration Using Nature Inspired Techniques

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ABSTRACT: *Automatic satellite image registration for multi-sensor images is becoming increasingly important to aid in flood damage assessment. We consider two images, the one before flood (optical image) and the other during flood (SAR image) in the registration process. The objective is to maximize the similarity metric (of these two images) using information theoretic measures such as Mutual Information (MI). The maximum MI would imply that the images are registered better. The function of these metric for transformation parameters are generally non-convex and irregular and, therefore, makes it difficult to use the standard optimization methods for the global solution. In this paper, we present the nature inspired techniques – Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Artificial Bee Colony (ABC) to search the maximum MI. From the results obtained, we compare the performance evaluation and conclude that the nature inspired techniques are accurate and reliable in solving the automatic satellite image registration.*

Keywords: Satellite Image Registration, Genetic Algorithm, Particle Swarm Optimization, Artificial Bee Colony

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1. Introduction

Floods occur in many regions of the world every year and cause great losses. In order to monitor and assess such situations, decision-makers need accurate knowledge of the real situation. How to provide actual information to make decision for flood monitoring and mitigating is becoming the important task for public welfare. Over-estimation of the flooded area leads to overcompensation to people, while under-estimation results in production loss and negative impacts on the population. Hence, it is important to access the flood damage accurately. Earth observation techniques can contribute towards flood hazard modelling and they can be used to assess damage to residential properties, infrastructure and agricultural crop s[24].

Over a period of time, to develop a flood assessment and damage estimation framework, the data involves before flood (optical image) and the during flood (SAR image) [24, 26]. These images can be registered for further processing and extraction. With the availability of high resolution optical images, it is possible to do a reasonably accurate estimate of the damage caused by floods [20].

Synthetic Aperture Radar (SAR) is an active microwave instrument, producing imagery of the Earth's surface in all weather, at any time instant. The reason it is unaffected is because (Satellite Imagery FAQ, 2009) the SAR is an active instrument; it produces the illumination to view the scene. Since it does not depend on any external illumination (like the sun) it can be used night or day. SAR uses microwave frequency radiation. Microwave radiation penetrates cloud and haze, so it can image the Earth's surface in all weather. A SAR image offers the dual advantages of any weather imaging and easy water body detection. During the flooding period, it is likely that satellite images need to tackle cloudy skies, thus active imagers like SAR are useful. However, since they read the reflected intensity, they do not allow for the easy detection of other features. Features with a rough texture such as edges and corners, moving water appear bright and smooth surfaces such as walls and still water appear dark. Thus we need another image to be able to detect such features. Optical image (LISS III) is very useful in this respect since they can be read and understood easily. For accessing the flood damage, using SAR image and optical image (LISS III), we need to geometrically and/or temporally align these images. This alignment process is known as image registration.

Image registration based on Mutual Information (MI) has been successfully implemented in medical diagnosis. For example computer-assisted Tomography (CT), Magnetic Resonance Imaging (MRI) and Ultrasound (US) image for treatment planning, in functional brain imaging, in brain atlases and mapping, etc. [13,30,27]. Also, in satellite image registration this method has been found to be suitable for SAR and optical image registration [9,16,22].

Absence of local spatial information in MI weakened the robustness of MI based registration, and local maxima in the MI registration function occasionally result in mis-registration [10]. Improvements have been suggested, such as combining mutual information with image gradient [13,30]. However, due to the abundant speckle noise, gradient is not an effective representation for SAR images. Therefore, the approaches presented in [12,28], in which image gradient provides spatial information for mutual information, is not suitable for SAR and SPOT image registration. Image registration based on MI is a non-linear optimization problem, and hence evolutionary computational techniques have been used in earlier studies [4,3,6]. In [22,25], MI is calculated based on swarm intelligence technique such as Particle Swarm Optimization by converging to global maxima.

Recently, researchers are interested in locating optimal solution of a given multi-modal function in a d - dimensional search space. For this purpose nature inspired techniques are used. [14] developed Artificial Bee Colony (ABC) based on foraging behaviour of honey bee. It is observed in the literature that ABC is more efficient in finding optimal solution comparing with other nature inspired techniques available in the literature [14].

In this paper, we present automatic satellite image registration using multi-sensor images. Here, we need to match them to relate the information from the two images. Image registration problem, in general, is maximizing the similarity metric between the given images. In this study, we attempt to match a SAR image with optical image (LISS III) using mutual information, with the aid of nature inspired techniques – Genetic Algorithm, Particle Swarm Optimization, and Artificial Bee Colony. Experimental results show that our approach is much more accurate. Finally, the performance of these registration methods are evaluated using quality measures [18] like Root Mean Square Error (RMSE), Peak Signal-to-Noise Ratio (PSNR) and percentagefit-error (PFE).

The paper is organized as follows: Section 2 introduces the concepts used, and the problem formulation using Mutual Information. Section 3 presents nature inspired techniques for image registration. Section 4 presents the simulation results obtained in our study. Conclusions are given in section 5.

2. Image registration process

The two dimension satellite images LISS III and SAR image has been used for registration in our study. The satellite image registration is generally performed to determine global alignment of SAR image [22]. Many nonlinear registration methods align small blocks of the floating image to the optical image in a linear manner [15]. Because of the difficulties such as non-linearity, we use nature inspired techniques in registration. In this study, the goal of the optimization is to determine the optimal values of t_x, t_y and θ, (decision variables), with the objective of maximizing the mutual information.

2.1 Similarity Metric (Objective Function)

Mutual information (MI) is defined for two random variables X and Y as

$$I(X,Y) = H(X) + H(Y) - H(X,Y) \tag{1}$$

H(X) and *H(Y)* are the entropy of the two random variables. The two are calculated from the marginal probabilities of the corresponding variables. $H(X,Y)$ is the joint entropy of the two random variables X and Y, calculated from the joint probability distribution of X and Y.

$$H(X) = -\sum_{x \in X} p_x \log(p_x) \tag{2}$$

$$H(Y) = -\sum_{y \in Y} p_{xy} \log(p_y) \tag{3}$$

$$H(X,Y) = -\sum_{x \in X} \sum_{y \in Y} p_{xy} \log(p_{xy}) \tag{4}$$

MI is a measurement for the statistical dependency between two images. If the two images are distributed similarly, then MI is high. It is a measure of the relative independence of two images [30]. High values indicate high dependence. The objective function for automatic satellite image registration must attain a global maximum at the correct registration [13,22]. Much of the current work on automatic satellite image registration utilizes information theoretic such as MI [9,16,22,25]. MI has been used for multi-sensor satellite image registration[16,22,25].

This paper discusses the registration of SAR image to an optical (LISS III) image. Initially knowing the resolution of both the image, the images are pre-processed to bring them more or less of the same scale and size, which is achieved using bicubic interpolation technique [29]. We consider only translation (in two directions t_x , and t_y) and rotation (θ) of the sensed image (SAR image) for registration purposes. Hence, our decision variables are t_x, t_y and $\theta_¸$. Translation has been limited to ± *50* pixels in both the directions and rotation is in the range ± 180^o .

Mathematically the problem is defined as:

Let the images be represented as: i. the before flood image: $I_b(x,y)$, LISS III image is a function of both x and y directions; ii. the during flood image: $I_s(x,y)$, SAR image which has to be matched is also a function of x and y directions and; iii. the image represented by each agent:

$$I'(k) = crop(rotate(Is\ (x - i, y - j)), \theta) \tag{5}$$

where $k = 1, 2, \ldots n$ represent the n agents used for searching the optimum position.

Then the function to be optimized is:

$$f = MI(I_b, I') \tag{6}$$

where MI is a function that computes the MI of the before flood image and the image represented by each agent.

The objective of the search is

$$Max\{f\} \tag{7}$$

Subjected to:

$-50 <= i, j <= 50$ *and*

$-180 <= \theta_¸ <= 180$

The image to be matched is translated in the two directions by i and j pixels respectively, and then rotated through $\theta_¸$ degrees. Theresulting image is cropped to maintain the image size. Joint probability, and consequently the mutual information, can only be calculated if the two images are of the same size, hence the need to maintain the number of pixel by cropping the image.

2.2 Optimization of similarity metrics

The standard optimization techniques, such as Powell's direction set method [2], conjugate gradient [17], Nelder–Mead simplex algorithm [2, 17], etc, are generally used in image registration. These methods still frequently become trapped in local optima [11]. Therefore, global optimization is often required. Recently, most widely used global approaches are nature inspired techniques.

Nature inspired technique is the field of research that works with computational techniques inspired in part by nature and natural systems. These nature inspired techniques provide a more robust and efficient approach for solving complex real-world problems [1]. Many nature inspired techniques such as Artificial Bee Colony (ABC) [14], Genetic Algorithm (GA) [8], Particle Swarm Optimization (PSO) [5] etc.. have been proposed. Since they are heuristic and stochastic in nature, they are less likely to get stuck in local minimum, and they are based on populations made up of individuals with a specified behaviour similar to biological phenomenon. These characteristics led of the development of nature inspired computation as it is increasingly applied in various domains (Engineering problems). Here, GA, PSO, and ABC methods are used for automatic satellite image registration.

3. Image registration using nature inspired techniques

We use three nature inspired techniques to solve the above problem namely Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Artificial Bee Colony (ABC).

3.1 Genetic Algorithm (GA)

Genetic algorithm is a population based evolutionary computation technique [8]. An initial population *N* is taken i.e. a random set of translation and rotation are assigned to the initial population. The fitness of the population is then evaluated according to the fitness function. A random selection of chromosomes from the current population is made. The selected chromosomes are then subjected to genetic operators where new translation and rotation are generated. The new population is then evaluated. This process goes on for *T* generations so as to achieve convergence. Three genetic operators are used namely crossover, mutation and reproduction. Each operator has a predefined probability to occur. The basic algorithm is summarized below:

1. The initial population is initialized randomly within the search space.

2. Fitness of each parent is evaluated according to the objective function. The objective function used is the mutual information between the two images (before and during flood image)

3. A random selection of two parents is made and they are subjected to genetic operations according to the probabilities. This is done for the full generation without selecting a parent twice.

4. The new generation thus formed is then evaluated and the global maximum is recorded.

5. The steps 2 and 4 are repeated for *T* generations or until convergence is observed.

3.2 Particle Swarm Optimization (PSO)

PSO is a population based swarm intelligence technique [5]. Each particle is assigned an initial position and velocity in the given search space. The particles then traverse through the search space depending on its fitness. The movement of the particles are governed by the position of their local bests and the global best in the given search space. The velocity and position after each iteration varies according to the following equations.

$$V_{id+1} = V_{id} + c_1 r_1 (\text{globalbest} - X_{id}) + c_2 r_2 (\text{localbest}_i - X_{id}) \tag{8}$$

$$X_{id+1} = X_{id} + V_{id} \tag{9}$$

where w is inertia; $d = (1,2,\ldots D)$; c_1 and c_2 are two positive constants; and r_1 and r_2 is a random number in the range [0,1].

These equations are computed repeatedly for each agent for the specified number of iterations. The number of iterations is large enough to allow most or all of the agents to converge at a point that the swarm detects as the most optimum point. The main steps of the procedure are:

1. Randomly distribute *N* agents in the search space. Assign a velocity vector in addition to the position vector to each agent.

2. A global best position is calculated from the current and previous positions of all the agents. This position has the most optimum value for the given objective function. Each agent also has a local best position associated to it. The objective function used is the mutual information between the two images (LISS III and SAR image, SAR image is translated and rotated by the coordinates of the agent in the search space).

3. From the current position and velocity, local and global best positions calculate the new velocity of each agent according to equation (8).

4. Update position as sum of previous position and new velocity according to equation (9).

5. Repeat steps 2 – 4 for specified number of iterations or until all points converge to a single location.

3.3. Artificial Bee Colony (ABC)

Artificial Bee Colony (ABC) [14] is a class of optimizing numerical problem based on swarm intelligence, investigating the foraging behaviour of bees. In ABC algorithm, the colony of artificial bees contains three groups of bees - scout bees, employed bees and onlookers. A bee carrying out random search is called a scout. A bee waiting on the dance area for making decision to choose a food source is called an onlooker and a bee going to the food source visited by itself previously is named an employed bee.

In a robust search process, exploration and exploitation process must be carried out together. In the ABC algorithm [14], the scout bees control the exploration process, while the employed bees and onlookers' carryout the exploitation process in the search space.

i) *Exploration phase:* For each solution x_{ij}, where $i = 1,2..n$ and j is dimensional vector. The scout bees explore a new food source with x*i*. This operation can be defined as in (10)

$$x^j_i = x^j_{min} + (x^j_{max} - x^j_{min}) * rand\ (0,1) \tag{10}$$

The population spread is restricted within the search space S i.e. $x_{ij} \in S$ and in the equation (10) x_{min} and x_{max} is the lower and upper limit respectively of the search scope on each dimension.

ii) *Exploitation phase:* In this phase, assuming the scout bees which have explored food source are selected as employed bees, which randomly perturb to the nearest neighbour, this produces a modification on the position (solution) in her memory depending on the local information (visual information) and tests the nectar amount (fitness value) of the new source (new solution). If the nectar amount of the new one is higher than that of the previous one, the bee memorizes the new position and forgets the old one. Otherwise it memorizes the position of the previous one. After all employed bees complete the search process; they communicate the nectar information of the food sources and their position information with the onlooker bees on the dance area. An onlooker bee evaluates the nectar information taken from all employed bees and chooses a food source with better nectar amount.

An artificial onlooker bee chooses a food source depending on the new positions, using the equation 11.

$$p_i = \begin{cases} x_i, if\,(f(x_i) \geq f(v_i)) \\ v_i, if\,(f(x_i) \leq f(v_i)) \end{cases} \tag{11}$$

In order to select the better nectar position found by an onlooker, O_b is defined as

$$O_b = arg_{pi}\ max\ f(P_i),\ i \leq i \leq n \tag{12}$$

where P_i is the best fitness value of the solution i which is proportional to the nectar amount of the food source in the position i and n is the number of food sources which is equal to the number of employed bees.

In order to produce a candidate food position from the old one in memory, the ABC uses the following equation (13):

$$v_{ij} = \alpha\, x_{ij} + (1 - \alpha)\,(x_{ij} - x_{kj}) \tag{13}$$

where $k=1, 2,...,n$ and $j=1, 2,...,D$ are randomly chosen indexes. Although k is determined randomly, it has to be different from i.

α is an adaptively generated random number. The food source of which the nectar is abandoned by the bees is replaced with a new food source by the scout bees. The main steps of the algorithm are as below:

1. Create a initial population of artificial bees within the search space x_{ij}

2. Evaluate the fitness of the population

3. while (stopping criterion not met)

3.1: Produce new solutions (food source positions) v_{ij} in the neighbourhood of x_{ij} for the employed bees using the equation (13)

3.2: Evaluate the fitness (MI) value and apply the selection process between x_{ij} and v_{ij} using equation (11) and (12)

3.3: Produce new solutions (new positions – translation and rotation) v_{ij} for the onlookers from the solutions x_{ij}, selected depending on P_i and evaluate them

3.4: Determine the abandoned solution (source) x_{ij}, if exists, and replace it with a new randomly produced solution x_{ij} for the scout bee using the equation (10)

3.5 Memorize the maximum MI value and its position (translation and rotation)

4. End While

4. Experimental results and discussion

We present the experimental results obtained for LISS III and SAR image registration problem. First, we describe characteristic of the satellite data and method of obtaining the ground truth to evaluate performance measures. Next we present experimental results obtained from nature inspired techniques for registration. Finally we present the comparison of registration methods and analyze their performance.

4.1 Satellite Image Acquisition

In our experimental study, the before and during flood image covering the scene Midnapore district which is 15 *km* North of Kharagpur, West Bengal, India is used. The riven seen in the satellite data is Subernareka River. The scene details are - i. before flood - LISS III image as shown in figure 1 of size 382 * 607, with resolution 23.5 *m*, Path/Row – 107/56 and Date of Pass (DOP) – 4th March 2002, ii. during flood - Radarsat 1 – Synthetic Aperture Radar (SAR) image as shown in figure 2 of size 180 * 315, with resolution 50 *m*, orbit 65927 ASC, beam mode: (B) W1, W2, S5, S6 and DOP: 21st June 2008.

Figure 1. LISS III (before flood) satellite image

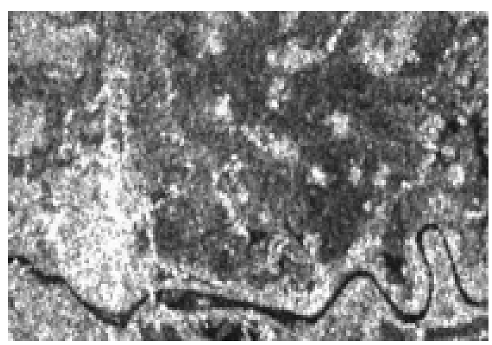

Figure 2. SAR (during flood) satellite image

The ground truth is prepared for the multi-sensor satellite image by visual inspection to align to a user defined ground control points. Automatic registration of images using MI was successfully carried out using nature inspired techniques. The ground truth alignment is used as reference to evaluate the performance of automatic satellite image registration using nature inspired techniques.

4.2 Performance measures

The performance of image registration algorithm is evaluated using three error estimation methods. The quality measures (Naidu et al., 2003) are computed to check the automatic image registration will match the result with a ground truth data. If *I* be the ground truth image and *I'* be the registered image (both of size $M * N$ pixels) and *L* be the total number of pixel intensity distribution which is 0 to 255 i.e. 256 for a given scale in image then,

i. *Root Mean Square Error (RMSE):* this will be closer to zero when the ground truth and registered image are similar. This will increase when the dissimilarity increases.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}[I(i,j) - I'(i,j)]^2}{MN}} \tag{16}$$

ii. *Peak Signal-to-Noise Ratio (PSNR):* This will be high when the ground truth and registered image are similar.

$$PSNR = -40\log_{10}\frac{RMSE}{L} \tag{17}$$

iii. *Percentage Fit Error (PFE):* This will be closer to zero when the ground truth and registered image are similar. This will increase when the registered image is deviated from the ground truth image.

$$PEF = \frac{(I - I')}{I} * 100 \tag{18}$$

4.3 Experimental Results

In this section, we discuss the experimental results obtained using nature inspired techniques for multi-sensor satellite image registration and compare the results with the performance measures. Initially, the image is pre-processed using bicubic interpolation technique [29] to bring both the image more or less of the same size and scale.

Parameter	MI for LISSIII and SAR image	Genetic algorithm	PSO algorithm	ABC algorithm
(t_x, t_y)	(0,0)	(-3,-17)	(-6,-17)	(-7,-18)
θ	0	1	1	1.5
Max MI	0.7105	0.8044	0.8057	0.8126

Table 1. Optimal MI value

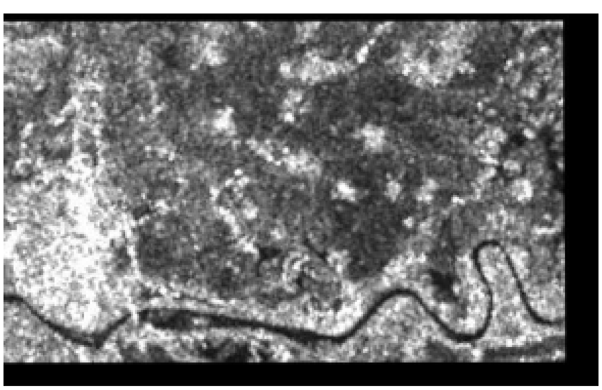

Figure 3. Registered SAR image

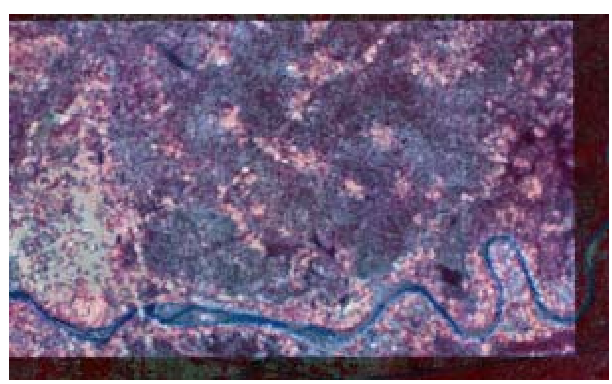

Figure 4. LISS III image is fused with the registered SAR image

From Table 1 we observe that before registration the MI value of LISS III (before flood) and SAR (during flood) image is 0.7105. For the registered image using nature inspired techniques, the MI value has increased. Figure 3 shows the final registered SAR image for the best MI value, which has been translated to the left and up by certain pixels and rotated by certain angle. Figure 4 is the LISS III image is fused with the registered SAR image.

4.3.1 Genetic Algorithm (GA)

We first start with a random distribution of population as the initial state and calculate its energy/fitness. The most favourable parameter values after different runs are as follows:

Population N = 100

Selection is random

Genetic operators: initial rate

Crossover rate: 70%

Mutation rate: 10%

Reproduction rate: 20%

Number of generations T = 20

For every generation the fitness of the current population is calculated. We follow an elitist approach in finding the optimal solution. The parent of the current population having the best fitness value is recorded. Therefore after T iterations the global best will have the fitness value of the best parent it has come across.

The number of function evaluations generated in GA algorithm can be obtained as follows: Let N be the size of initial population, S_r is the probability of reproduction, S_c is the probability of crossover, S_m is the probability of mutation, and T is the maximum number of generation. Then the number of solutions generated is $N * S_r * T + N * S_c * T + N * S_m * T$. In our studies, we have used 20 as the maximum number of generations, but we observe that the optimal solution is reached around the 16 generation. The number of function evaluation for image registration, (with $S_r = 0.2$, $S_m = 0.1$, $S_c = 0.7$, $N = 100$ and $T = 20$) in one simulation run are 2000.

4.3.2 Particle Swarm Optimization

All the particles are randomly initialized within search space. The experimental conditions for most favourable parameter value after different runs are as follows:

Number of particles N = 50

Number of iterations T = 20

Cognitive learning rate c1 = 2

Social learning rate c2 = 2

Inertia factor ω = 0.5

Initially all the particles are randomly placed in the specified space and given random velocities. Each particle is associated with a string of translation and rotation points. The fitness of the particles for T iterations i.e. at each iteration MI is evaluated and the particle having the best fitness is recorded.

The number of function evaluations generated in PSO algorithm can be obtained as follows: Let N be the size of initial population, and T is the maximum number of generation. Then the number of solutions generated is $N * (1 + T)$. In our studies, we have used 20 as the maximum number of generations, but we observe that the optimal solution is reached around the 3 generation. The number of function evaluation for image registration, (with $N = 50$ and $T = 20$) in one simulation run are 1050.

4.3.3 Artificial Bee Colony

The Artificial Bee Colony algorithm is also population based swarm intelligence method. The bees are randomly initialised. The most favourable parameter values after different runs are as follows:

Number of bees N = 50
Number of generations T = 20
Randomness Amplitude of bee α = [1,…,0.4], adaptively allocated
(decreasing from 1 to 0.4 with each iteration)
Learning rate β = [1,…,0.4], adaptively allocated
(decreasing from 1 to 0.4 with each iteration)

After initializing the population the fitness of all the employed bees are calculated. Out of the current population having a high fitness value are selected. The selected employed bees are searched locally by perturbing to nearest location using the parameter α. A starting value of α = 1 is used to initially accommodate a more global search and is dynamically reduced to α = 0.4.

The number of function evaluations in ABC algorithm can be obtained as follows: Let N be the size of initial population, and T is the maximum number of generation. Then the number of solutions generated is $2 * N * (1 + T)$. In our studies, we have used 20 as the maximum number of generations, but we observe that the optimal solution is reached around the 16 generation. The number of function evaluation for image registration, (with N =5 0 and T = 20) in one simulation run are 2100.

4.5 Comparison of nature inspired techniques

Since the problem is NP-hard using nature inspired techniques is an effective way to achieve optimal or near-optimal solutions for real-world problems [7].

Problem	Optimal	Worst	Mean	Standard Deviation	CPU time (Seconds)
GA	0.8044	0.7528	0.782415	0.0165716	86.26
PSO	0.8057	0.8009	0.80513	0.0010921	39.55
ABC	0.8126	0.8046	0.807685	0.0023903	39.17

Table 2. Results of nature inspired techniques after 20 runs for optimal MI value

From Table 2, we can observe in comparison with other nature inspired techniques the results obtained using GA and PSO is not optimal in comparison with that of ABC. Being a continuous optimization problem every possible translation and rotation picked by the population at each iteration is not the optimal based on the perturbation of the best point within its limit. Therefore results got using GA and PSO are not optimal. On the other hand ABC provide us with optimal results as the search space is effectively scanned for optimal results which can be seen in Figure 5. In case of ABC, at two level searching operation is taken care by the employed and onlooker bee which helps the algorithm always to converge to global maxima. ABC searches globally optimal value and further perturb within global value to find better optimal solution. We can also observe in Table 2, that mean value after 20 runs PSO, and ABC are closer to the optimal MI value as searching is consistent in these technique compared with GA. The experiments were conducted on Intel(R) Core(TM) i7 CPU with 4 GB of RAM, and windows XP system using Matlab 7.6. The CPU time taken to converge is fast in case of PSO, and ABC in comparison with that of GA. In literature, to find optimal solution for a given problem, researchers have analyzed and compared different nature inspired techniques and concluded ABC performs better [19,22].

The performance measure of the image registration has been evaluated and listed in Table 3. From this table we can observe that before registration when the LISS III and SAR image is evaluated along with the ground truth image the RMSE, PSNR and PFE are not optimal in comparison with that of registered image using nature inspired technique. An empirical evaluation process developed has provided a RMSE about 0.4131 for PSO, and ABC in comparison with that of GA with RMSE value 0.4418. The PFE is 0.1605, in the case of ABC where as PSO and GA has 0.1663 and 0.1996 respectively.

From Table 2 we can observe that mean value after 20 runs incase of GA to pick optimal MI value is inconsistent comparing with that of other nature inspired techniques. Further to depict the use of performance measures for maximum MI value using automatic image registration. We selected GA as case study as it has lot of variation in converging to MI value. For this variation of MI obtained result we calculated RMSE, PSNR and PFE, as shown in table 4. From this table we can observe that as MI value

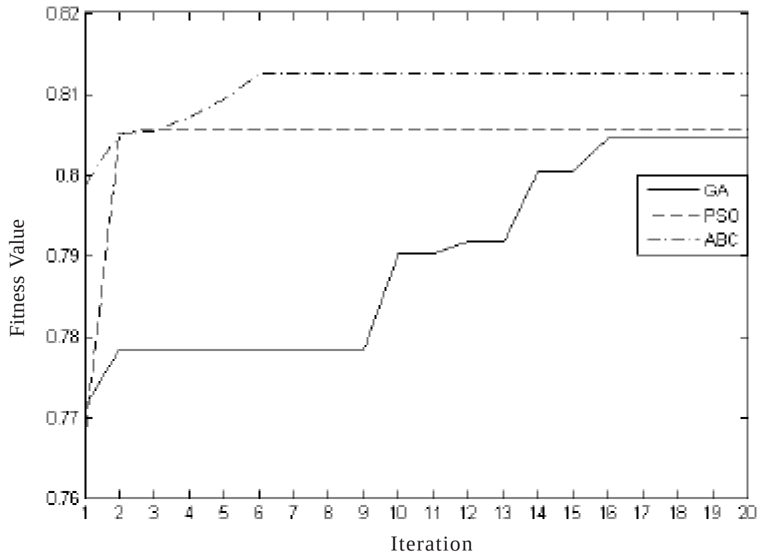

Figure 5. Variation of MI with each iteration

Nature Inspired Techniques	LISSIII Image with Ground truth	SAR with truth	Image Ground	GA	PSO	ABC
				Registered Image		
MI	-	-		0.8044	0.8057	0.8126
RMSE	0.86	0.55		0.4418	0.4131	0.4131
PSNR	79.47	53.27		55.26	55.84	55.84
PFE	0.4973	0.4973		0.1996	0.1663	0.1605

Table 3. Performance Evaluation of nature inspired technique for optimal MI value

Translation (tx,ty)	Angle(q)	MI	RMSE	PSNR	PFE
(5,-12)	-5	0.7528	0.5126	53.96	0.2628
(2,-4)	4	0.7678	0.4777	54.58	0.2598
(1,-20)	-6	0.7794	0.4763	54.61	0.2409
(-2,-18)	3	0.7870	0.4562	54.98	0.2259
(-2,-16)	-3	0.7944	0.4497	55.11	0.2164
(-3,-17)	1	0.8044	0.4418	55.26	0.1996

Table 4. Performance Evaluation of Genetic Algorithm

increases RMSE and PFE decreases where as PSNR decreases. These empirical evaluations indicate that although the images are from different sensors, MI is still a valid metric to measure the degree of match between the images.

The convergence plot (Figure 5) shows us the rate of convergence of the different algorithms, out of 20 runs we selected the one which has converged to optimal value. We see that PSO, and ABC converges very quickly compared to GA. Though PSO has converged faster with in 3rd iteration, the value 0.8057 is not optimal in comparison with that of ABC.

5. Conclusions

In this paper, we present an approach for registering a SAR image with an LISS III image using the concept of mutual information. This value is optimized using nature inspired techniques instead of calculating the mutual information for all possible angles of rotation and translation thus speeding up the process. In our experiment we observed ABC proved to be better technique to find maximum MI for better registration. The performance of these registration methods are evaluated using quality measures. The empirical evaluations of quality measure indicate that although the images are from different sensors, maximization of MI is still a valid metric to measure the degree of match between the images. Some of the observations of this study, for registering during flood image with before flood image all the nature inspired techniques achieves better solutions in terms of higher MI, which proves the quality of our approach.

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