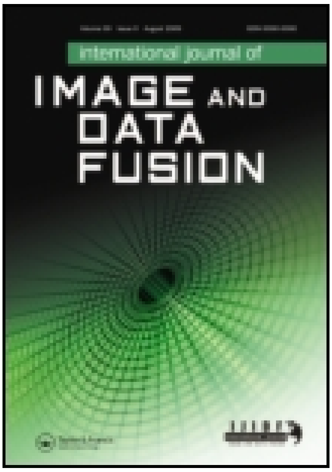

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RESEARCH ARTICLE

Automatic registration of multi-temporal remote sensing images based on nature-inspired techniques

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In this article, we present nature-inspired techniques for automatic image registration of multi-temporal satellite images. Multi-temporal satellite image registration is becoming increasingly important to aid in flood damage assessment. We consider two images in the registration process: one before-flood image and another during-flood image. The objective is to maximise 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 better registered. The function of these metrics for transformation parameters is generally non-convex and irregular and, therefore, makes it difficult to use standard optimisation methods for the global solution. In this study, nature-inspired techniques – genetic algorithm (GA), particle swarm optimisation (PSO) and firefly algorithm (FA) are used to search for the maximum MI. The multi-temporal images – Linear Imaging Self-Scanning Sensor III (LISS III) image (before flood) and Synthetic Aperture Radar (SAR) image (during flood) and Moderate Resolution Imaging Spectroradiometer (MODIS) images (before and during flood) are used to demonstrate the performance of the proposed image registration approach. From the results obtained, we compare performance evaluations and conclude that nature-inspired techniques are accurate and reliable in solving satellite image registration.

Keywords: mutual information; genetic algorithm; particle swarm optimisation; firefly algorithm

1. Introduction

Every year floods occur in many regions of the world 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 decision makers for flood monitoring and mitigation is an important task for public welfare. Over-estimation of a flooded area can lead to over-compensation to people, while under-estimation results in production loss and negative impacts on the population. Hence it is essential to assess the flood damage both accurately and quickly. Earth observation techniques can contribute towards flood hazard modelling and can also be used to assess damage to residential properties; infrastructure and agricultural crops (Wang *et al.* 2002, Sande *et al.* 2003). To analyse flood-prone regions, multi-temporal satellite images are used to compare both normal and heavy monsoon/flood conditions. In the literature, the before-flood images used are Moderate Resolution Imaging Spectroradiometer (MODIS) and Linear Imaging Self-Scanning

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Sensor III (LISS III), and during-flood images used are MODIS and Synthetic Aperture Radar (SAR) (Brakenridge and Anderson 2006, Schumanna *et al.* 2011).

The freely and readily available data from NASA's MODIS satellite sensor have considerable potential for applied hydrology applications such as flood detection, characterisation and warning, flood disaster response and damage assessment, and flood disaster mitigation. Although MODIS is a low-resolution image sensor (with a spatial resolution of 250–1000 m), it can provide excellent land/water discrimination (Brakenridge and Anderson 2006). To support change detection analysis, images are aligned in order to minimise the effect of errors that typically limit the overlay of multiple date images (post classification) (Lunetta *et al.* 2006).

SAR is an active microwave instrument, producing imagery of the Earth's surface under any weather, at any time. The reason it is unaffected is because SAR is an active instrument; it produces the illumination to view the scene (Satellite Imagery 2013). Since it does not depend on any external illumination (like the sun), it can be used both night and day. SAR uses microwave frequency radiation. Microwave radiation penetrates the clouds and haze; hence, it can image the Earth's surface in all weather conditions. The SAR instrument offers the dual advantages of any weather imaging and easy water body detection. During a flooding period, it is likely that satellite images need to tackle cloudy skies. Therefore, active images like SAR are useful. However, since SAR images read the reflected intensity, they do not allow for an easy detection of other features. Features with a rough texture such as edges and corners (including moving water) appear bright, and smooth surfaces such as walls and still water appear dark. Thus, another image type is needed to be able to detect such features. LISS III images are very useful in this respect since they can be read and understood easily. For assessing flood damage, using SAR and LISS III images, it is necessary to geometrically align these images. The alignment process is known as image registration.

Image registration methods are classified into two broad categories, namely *area-based methods* and *feature-based methods*. Feature-based methods are appropriate in situation where edges and points are clearly detected on both the images to be registered. However, that is not the case in all situations. On the other hand, area-based methods are useful when there is an absence of clearly detected edges or points in both the images that are to be registered (Fonseca and Manjunath 1996). Area-based methods operate under the assumption that a strong relationship exists between the distributions of the features in the images to be registered. They attempt to match values in the feature distributions by using mutual information (MI), correlation or other probabilistic information (Zitová and Flusser 2003).

Image registration based on MI has been successfully implemented in medical diagnosis, e.g., in computer-assisted tomography (CT), magnetic resonance imaging (MRI) and ultrasound (US) image for treatment planning, in functional brain imaging and in brain atlases and mapping (Zitová and Flusser 2003, Pluim *et al.* 2003, Wachowiak *et al.* 2004). Also, in satellite image registration this method has been found to be suitable for SAR and optical image registration (Inglada and Giros 2004, Lixia *et al.* 2005, Falco *et al.* 2008).

The 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 (Jeffrey 2003). Improvements have been suggested, such as combining MI with image gradients (Pluim *et al.* 2000, Wang and Tian 2005). However, due to the abundant speckle noise, gradients are not effective for SAR images. Therefore, the approaches presented in Pluim *et al.* (2000) and Wang and Tian (2005), in which image gradient provides spatial information for MI, are not suitable for SAR and Satellite Pour l'Observation de la Terre image registration. Image registration based on MI is a highly non-linear optimisation problem, and hence evolutionary computational techniques have been attempted in earlier studies (Fitzpatrick *et al.* 1984, Dasgupta and McGregor 1992, Ou *et al.* 1996, Chalermwat and El-Ghazawi 1999, Oh *et al.* 2006, Calderon *et al.* 2007). MI-based satellite image registration mainly depends on three important considerations (Pluim *et al.* 2003):

(1) The *search space* is all the possible combination of potential transformations that are used to align the images. But in practical implementations, to determine the search space, we consider the smallest increment and the range of each decision variable. In this study, two translations (t_x, t_y) and a rotation (θ) are used as decision variables.
(2) The *similarity metric* is an indicator of how closely the features are distributed between the two images. The most commonly used similarity metrics are based on information theoretic measures.
(3) The *search strategy,* which may include local search or global search, is used to optimise the similarity metric. The optimisation techniques can be gradient-based (Pluim *et al.* 2000, Jeffrey 2003) or population-based techniques (Talbi and Batouche 2004, Wachowiak *et al.* 2004).

A different class of population-based techniques called nature-inspired techniques, which include genetic algorithm (GA), particle swarm optimisation (PSO) and firefly algorithm (FA), can provide a set of potential solutions and also identify the optimal solution through collaboration and contest among the individuals in the population (Yang 2008). These techniques show a better convergence to the global optimum in comparison with traditional optimisation methods, which are prone to stop at local optima (Yang 2008). Therefore, nature-inspired algorithms have recently become more popular than conventional optimisation methods because of their simplicity, parallelism and quick convergence of the population towards the best solution in a given search space (Goldberg 1989, Omkar *et al.* 2011, D'Souza *et al.* 2012).

A GA is one family of adaptive search methods and has been used in image registration applications (Troglio *et al.* 2008, Senthilnath *et al.* 2014). In Talbi and Batouche (2004), where MI has been calculated based on nature-inspired technique such as PSO by converging to a global maximum. Further, various population-based methods (nature-inspired methods) have been applied and compared for image registration based on normalised cross correlation (Zhang and Wu 2012).

In this article, we present multi-temporal image registration for before-flood and during-flood satellite images. It has been demonstrated for remote sensing images that affine transformations are sufficient to register satellite images (Chen *et al.* 2014). Affine transformations take care of three measures, namely, translation, rotation and scaling. In our study, we use two image sets, where in each case, one image was acquired before a flood (reference image) and the other during a flood (sensed image). In both the cases there is an absence of edges or points. Here, we need to match the two images to relate the information from them. The image registration problem, in general, is to maximise the similarity metric between the given images. In this study, we attempt to match the multi-temporal satellite images using MI, with the aid of nature-inspired techniques – GA, PSO and FA. Experimental results show that our approach is efficient. Finally, the performances of these registration methods are evaluated using two quality measures (Naidu *et al.* 2003): root mean square error (RMSE) and percentage fit error (PFE). Two typical cases are considered to demonstrate the performance of the proposed multi-temporal satellite image registration – LISS III image (before flood) and SAR image (during flood) from the north of Kharagpur, West Bengal, India, and MODIS images (before and during flood) from the southern part of India.

The article is organised as follows: Section 2 introduces the concepts used and the problem formulation using MI. Section 3 briefly describes three nature-inspired techniques for image registration, and Section 4 presents their performance evaluations. Section 5 presents the experimental results obtained in our study, followed by the conclusions in Section 6.

2. Image registration process

In this section, we discuss the registration process using multi-temporal satellite images. Let M denote the spatial transformation that maps features (spatial locations) from one image to another image. Let I_{A} and I_{B} denote spatial locations in images A and B, respectively. The image registration problem is to determine M so that the mapping $M : I_{\mathrm{A}} \rightarrow I_{\mathrm{B}} \Leftrightarrow M(I_{\mathrm{A}}) = I_{\mathrm{B}}$ results in the 'best' alignment of A and B (Hill *et al.* 2001). Because digital images are sampled on a discrete grid, but M generally maps to continuous values, interpolation of intensities is required (Hill *et al.* 2001).

Although spatial transformations are more realistic, satellite image registration is generally performed to determine the global alignment of SAR images. In many non-linear registration methods, the images are progressively subdivided and locally registered (Likar and Pernuš 2001). The main challenge involves locating a global optimum in non-linear distribution of search space; hence, we use nature-inspired techniques in registration. In this study, the goal of the optimisation is to determine the optimal values of decision variables, i.e., for translation and rotation (t_x, t_y and θ), with the objective of maximising the MI.

2.1. Similarity metric (objective function)

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 entropies of the two random variables. They 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.

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

$$H(Y) = -\sum_{y \in Y} P_y \log(P_y), \tag{3}$$

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

where P_x and P_y are the marginal probability function and P_{xy} is the joint probability function.

MI is a measure of the relative dependency between the two images (Zitová and Flusser 2003). If the two images are distributed similarly, then MI is high. If the images are independent then MI is zero. High values indicate high dependence. The objective function for satellite image registration must attain a global maximum when the registration is correct (Wachowiak *et al.* 2004). Much of the current work on automatic satellite image registration utilises information theoretic measures such as MI (Inglada and Giros 2004, Talbi and Batouche 2004, Lixia *et al.* 2005). MI has been used for multi-sensor satellite image registration (Talbi and Batouche 2004, Lixia *et al.* 2005).

This article discusses the registration of multi-temporal MODIS images and the registration of multi-sensor SAR image to an LISS III image. For multi-sensor images, the images can be pre-processed to bring them more or less to the same scale and size, which is achieved using a bi-cubic interpolation technique (Zhiwei *et al.* 2009). Here, we consider only the translation (in two directions t_x and t_y) and rotation (θ) of the sensed image for the registration. Hence, our decision variables are t_x, t_y and θ. The objective function is the MI of the two images. The two axes of translation and one axis of rotation form the search space. If the coordinates of an agent in the search space is (i, j, θ), then i and j refer to the translations of the sensed image in two directions (up-down and left-right) and θ is the angle of rotation of the image.

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

$$I'(k) = R(I_s(x-i, y-j)), q) \tag{5}$$

where R is a rotation function and $k = 1, 2, \ldots, n$ represent the n agents used for searching the optimum position.

Then the function to be optimised is:

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

where m 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 thus

$$\text{Maximize}\, f. \tag{7}$$

The image to be matched is translated in the two directions by i and j pixels, respectively, and then rotated through θ degrees. The resulting image is cropped to maintain the image size. The joint probability, and consequently the MI, 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.

This image is then compared with the before-flood image using MI to check if they match. The objective of any nature-inspired techniques for image registration is to increase the MI stochastically (Talbi and Batouche 2004). A large value of MI occurs if the two images have good geometric alignment. When the two images are aligned, the uncertainty about one image is reduced, if we know the other image and we can say with more confidence what during-flood image will look like, given the before-flood image or vice versa.

2.2. Optimisation of similarity metrics

The standard optimisation techniques, such as Powell's direction set method (Bernon *et al.* 2001), the conjugate gradient (Maes *et al.* 1999), and the Nelder–Mead simplex algorithm (SA) (Press *et al.*, 1994, Maes *et al.* 1999, Bernon *et al.* 2001) are generally used in image registration. These methods still frequently become trapped in local optima (Jenkinson and Smith 2001). Therefore, global optimisation is often required. Recently, the most widely used global approaches for highly non-linear problems are nature-inspired techniques.

Nature-inspired techniques form a field of research 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 (Bäck and Schwefel 1993, Yao 1999). Many nature-inspired techniques such as GA (Goldberg 1989), PSO (Eberchart and Kennedy 1995), and FA (Yang 2010) have been proposed. Since those methods are heuristic and stochastic in nature, they are less likely to get stuck in local optima. Furthermore, they are population-based, mimicking certain successful characteristics in nature or natural systems. These metaheuristic algorithms have been widely used in many applications and areas such as engineering design. Here, GA, PSO and FA methods are used for automatic satellite image registration.

3. Image registration using nature-inspired techniques

We now use three nature-inspired techniques, namely GA, PSO and FA, to solve the image registration problem.

3.1. Genetic algorithm

GAs are a class of population-based, evolutionary computation techniques (Goldberg 1989, Omkar *et al.* 2011, D'Souza *et al.* 2012, Senthilnath *et al.* 2012a, 2013a). An initial population N can be initialised, 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, including crossover, mutation and reproduction of the fittest. Each operator has a predefined probability to occur. The basic algorithm is summarised below:

(1) The initial population is initialised randomly within the search space.
(2) Fitness of each parent is evaluated according to the objective function. The objective function used is the MI between the two images (before-flood image 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 current global best solution is recorded.
(5) The steps 2 and 4 are repeated for T generations or until convergence is observed.

3.2. Particle swarm optimisation

PSO is a population-based swarm intelligence technique (Eberchart and Kennedy 1995, Omkar *et al.* 2009, Senthilnath *et al.* 2011a, 2011b, 2013b). Each particle is assigned an initial position and velocity in the given search space. The particles then traverse through the search space depending on their fitness. The movement of the particles are governed by the position of the locally best and the globally best particles in the given search space. The velocity and position after each iteration vary, according to the following equations:

$$V_{(id+1)} = wV_{id} + [C_1 r_1(\text{localbest}_i - X_{id})] + [C_2 r_2(\text{globalbest} - X_{id})] \tag{8}$$

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

where w is the inertia; $d = (1, 2, \ldots, D)$ is dimension; 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 updated 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) The current globally 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.
(3) Each agent also has a local individual best position associated to it, which denotes the location of the most optimum position that the agent has been in so far. The objective function used is the MI between the two images (before- and during-flood images; the during-flood image is translated and rotated by the coordinates of the agent in the search space).
(4) From the current position and velocity, the local and global best positions are used to calculate the new velocity of each agent according to Equation (8).
(5) Update position as sum of previous position and new velocity according to Equation (9).
(6) Repeat steps 2–5 for specified number of iterations or until all points converge to a single location. This is the optimal point.

3.3. Firefly algorithm

Fireflies use luciferin chemical to produce natural light. An important and interesting behaviour of fireflies is to produce brighter light mainly to attract prey and to communicate with others. Each firefly moves towards a neighbouring firefly that produces brighter light (Yang 2008).

The FA (Yang 2008, 2010, 2011, 2013, Senthilnath *et al.* 2011c) belongs to a class of algorithms that find the global optima of multi-modal objective functions based on swarm intelligence, investigating the foraging behaviour of fireflies. In the FA, agents or fireflies are randomly distributed in the search space. Agents are thought of as fireflies that carry a luminescence quality, called luciferin, that emit light proportional to this value. Each firefly is attracted by the brighter light intensity of other neighbouring fireflies (Yang 2008).

Initially, all the agents are randomly dispersed across the search space. The two phases of the FA are:

(1) *Light intensity variation phase:* here the intensity level of light content of the firefly is related to its objective function value. For a given maximisation problem, a firefly will attract another firefly proportional to its light intensity that is also proportional to the objective function. Consider a swarm of n fireflies. Let x_i denote a position for a firefly i and $f(x_i)$ represent x_i's fitness value

$$I_j = f(x_j), \quad 1 \leq j \leq n \tag{10}$$

where I_j is the brightness of firefly j for a given position x and fitness value $f(x_j)$.

(2) *Movement phase:* during the movement phase, each firefly decides, to move towards a neighbouring firefly that has a light intensity value more than its own. That is, they are attracted to neighbours that produce brighter light. As a firefly's attractiveness is proportional to the light intensity seen by adjacent fireflies, we can now define the attractiveness β of a firefly by

$$\beta = \beta_0 e^{-\gamma r^2} \tag{11}$$

where β_0 is the attractiveness at $r = 0$ and γ a fixed light absorption coefficient.

Now, to calculate the distance between any two fireflies i and j at position x_i and x_j, cartesian distance is given by

$$r_{ij} = \|x_i - x_j\| \tag{12}$$

The position $x_i(t + 1)$ of a firefly i attracted to another firefly j located at x_j is updated as

$$x_i(t+1) = x_i(t) + \beta_0 e^{-\gamma r_{ij}^2}[x_j(t) - x_i(t)] \tag{13}$$

For the purpose of finding a global maximum, the main steps of the FA are as given below:

(1) Deploy agents or fireflies randomly in the search space, assign each firefly with light intensity using Equation (10)

(2) For each agent:
  (2.1) Update the light intensity content of each firefly according to the current position
  (2.2) Move a step distance in the direction of the chosen firefly that has higher fitness value using Equation (13)
  (2.3) Memorise the best firefly fitness value (MI) and its position (translation and rotation)
(3) Repeat step 2 for a specified number of iterations

4. Performance measures

The performance of all image registration algorithms is evaluated using two error estimation methods. Quality measures (Naidu *et al.* 2003) are computed to check the automatic image registration to match the result with ground truth data. If I_G be the ground truth image and I_R be the registered image (both of size $M \times N$ pixels),

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

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left[I_G(i,j) - I_R(i,j)\right]^2}{MN}} \tag{14}$$

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

$$\mathrm{PFE} = \frac{(I_G - I_R)}{I_G} \times 100 \tag{15}$$

The RMSE and PFE are calculated with different sets of manually registered images and automatically registered images; consequently we obtain the average RMSE and PFE values. This is done in order to minimise the error in manually aligned image which is used as the ground truth image.

5. Experimental results and discussion

In this section, we present the results obtained for the multi-temporal satellite image registration problem. In our study, we consider two cases: first case, LISS III image (before flood) and SAR image (during flood), and the second case, before- and during-flood MODIS images for registration. First, we describe characteristics of the satellite data and experimental results obtained from nature-inspired techniques for registration. Then, we present the comparison of registration methods and analyse their performance.

Image registration can be carried out using area-based and feature-based methods in order to capture the geometric variation between two satellite images. Feature-based methods are most appropriate in situations where edges and points are clearly detected on both images that are to be registered. However, edges and points are not clearly detected on both images in all cases. In our study, two image sets are used, where one image is acquired before a flood (reference image) and the other during a flood (sensed image), where there is an absence of edges or points. Hence, area-based method would be more suitable for image registration in such cases. The main focus of this study is how to overcome the challenge of registering a during-flood image to a before-flood image and also use nature-inspired methods for finding a maximum MI to improve the image registration.

5.1. Case 1 – LISS III and SAR image

In our experimental study, the before- and during-flood images cover the scene Midnapore district which is 15 km North of Kharagpur, West Bengal, India. The scene 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, Path/Row – 107/56 and Date of Pass (DOP) – 4 March 2002; (ii) during flood: Radarsat 1 –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 – 21 June 2008 (Senthilnath *et al.* 2012a).

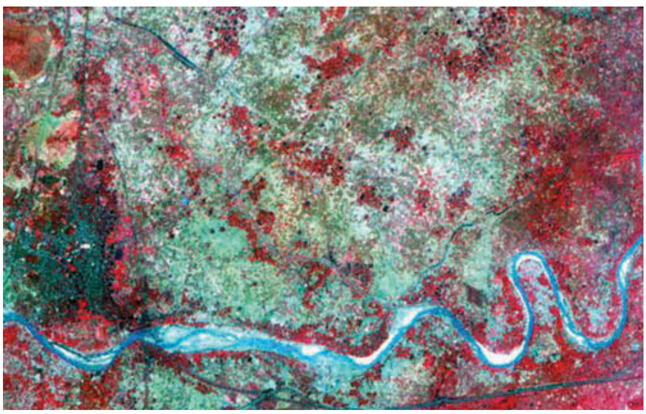

Figure 1. LISS III (before flood) satellite image.

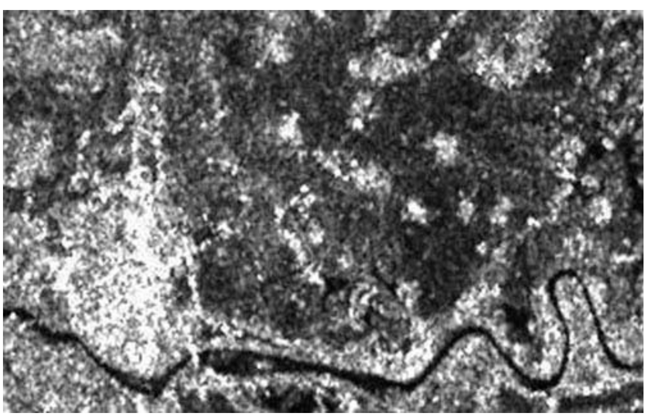

Figure 2. SAR (during flood) satellite image.

5.1.1. *Image registration using LISS III and SAR image*

Initially, the image is pre-processed using bi-cubic interpolation technique (Zhiwei *et al.* 2009) to make both the images more or less of the same size and scale.

From Table 1, we can 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 registered SAR image, overlaid on the LISS III image.

The performance measure of the image registration has been evaluated and listed in Table 2. From this table, we can observe that before registration (for the LISS III and SAR images) is evaluated along with the RMSE and PFE are not optimal in comparison with that of registered image using nature-inspired techniques. Table 3 details the comparison of nature-inspired techniques for 20 independent runs.

5.1.2. *Genetic algorithm*

We first start with a random distribution of population as the initial state and calculate its fitness value. For every generation the fitness of the current population is calculated. We follow an elitist approach in finding the optimal solution. The best fitness value of the current population is recorded. Therefore, after T iterations, the globally best individual

Table 1. Optimal MI value using LISS III (before flood) and SAR image (during flood).

Parameter	MI for LISSIII and SAR image	GA	PSO	FA
(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

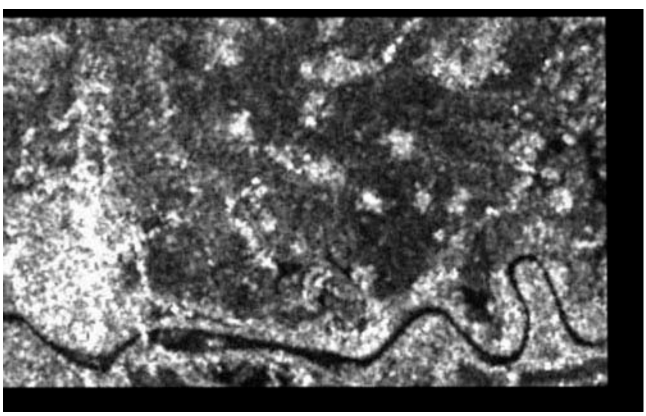

Figure 3. Registered SAR image.

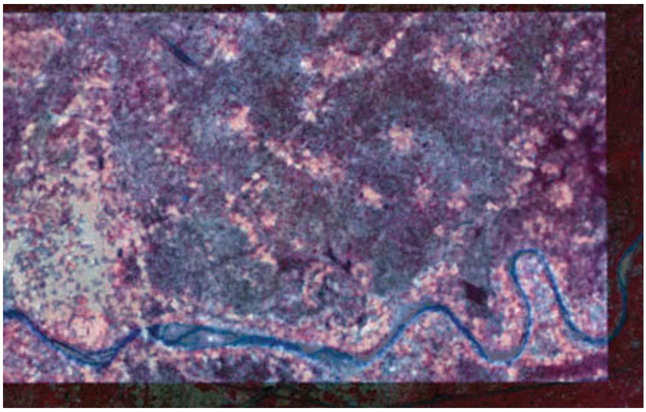

Figure 4. Registered SAR image is overlaid on the LISS III image.

Table 2. Performance evaluation of nature-inspired technique using LISS III (before flood) and SAR image (during flood).

Performance measures	LISS III image with ground truth image	SAR image with ground truth image	Registered image			
			SA (Press *et al.* 1994)	GA	PSO	FA
MI	–	–	0.7088	0.8044	0.8057	0.8126
RMSE	0.86	0.55	0.8165	0.4418	0.4131	0.4131
PFE	0.4973	0.4973	0.4407	0.1996	0.1663	0.1605
Time (s)	–	–	9.356	86.262	39.551	39.939

Table 3. Results of nature-inspired techniques after 20 runs using LISS III (before flood) and SAR image (during flood).

Nature-inspired techniques	Optimal	Worst	Mean	Standard deviation
GA	0.8044	0.7528	0.7824	0.0166
PSO	0.8057	0.8009	0.8051	0.0011
FA	0.8126	0.8019	0.8076	0.0026

will have the best obtained fitness value during the iteration history. The population is then subjected to genetic operations. The parent with the highest fitness value in the current generation will be passed onto the next generation.

The number of function evaluations or the number of solutions generated in GA 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 $((N \times S_r \times T) + (N \times S_c \times T) + (N \times S_m \times T))$.

After several runs, the following parameters were empirically selected for our experiments.

Population (N) = 50
Crossover rate (S_c) = 0.7
Mutation rate (S_m) = 0.1
Reproduction rate (S_r) = 0.2
Number of generations (T) = 20

5.1.3. Particle swarm optimisation

All the particles are randomly initialised within search space. 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, i.e., MI is evaluated, and the particle having the best fitness is recorded. The change in velocity and position of the particles are then calculated. The particles are then assigned new translation and rotation, and their fitness is evaluated which continues for T iterations.

The number of function evaluations generated in the 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 ($N(1 + T)$).

After several runs, the following parameters were empirically selected for our experiments.

Number of particles (N) = 50
Cognitive learning rate (c_1) = 2
Social learning rate (c_2) = 2
Inertia factor (ω) = 0.5
Number of iterations (T) = 20

5.1.4. Firefly algorithm

The FA is a population-based swarm intelligence method. The fireflies are initialised randomly in the search space. After the fireflies are deployed randomly in the search space, the attractiveness and light absorption coefficient values are used by the agents to update the locations of fireflies. Initially, after random initialisation, at each iteration the fireflies are moved towards a neighbouring firefly that has brighter light intensity, and then the fitness value of the fireflies are evaluated. This process continues until all the fireflies converge to the same translation and rotation value.

The number of function evaluations in FA 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 $\{[N(N-1)]/2\}T$.

After several runs, the following parameters were empirically selected for our experiments.

Number of firefly (N) = 50
Attractiveness (β_0) = 1
Light absorption coefficient (γ) = 1
Number of generations T = 20

5.2. Case 2 – MODIS image

In our study, we have used a MODIS surface reflectance product, i.e., MOD09Q1 terra surface reflectance, 8-day L3 global with a spatial resolution 250 m. The chosen study area is in the region surrounding the Krishna river located in South India. The size of the image is 482 × 627. The multi-temporal MODIS images are from different time periods: before a flood (March 2009) and during a flood (September 2009), as shown in Figures 5 and 6, respectively (Senthilnath *et al.* 2012b).

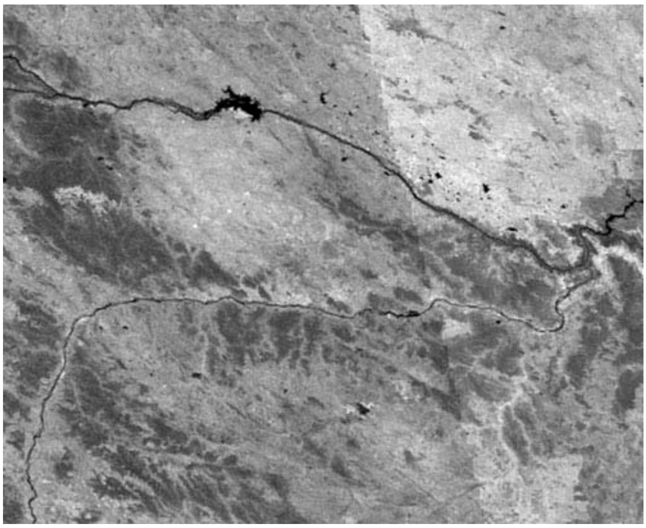

Figure 5. MODIS (before flood) satellite image.

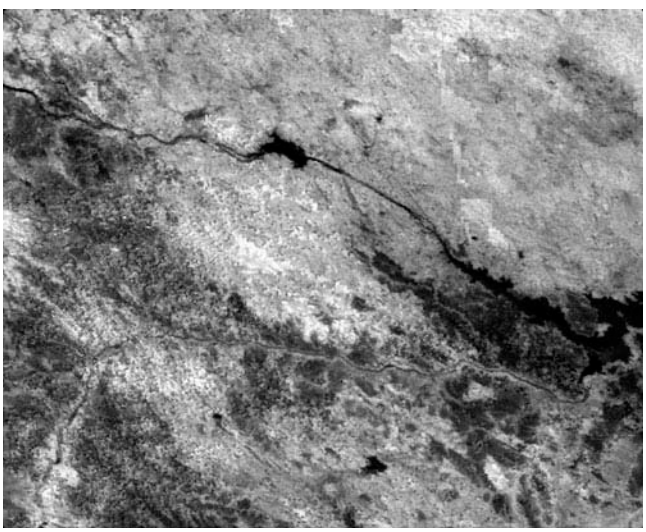

Figure 6. MODIS (during flood) satellite image.

5.2.1. Image registration using MODIS images

The MODIS image of before-flood is used as reference image to align the during-flood image. From Table 4, here also we can observe that before the registration process the MI value of before-flood and during-flood image is 0.2297. For the registered image using nature-inspired techniques, the MI value has increased. Figure 7 shows the final registered MODIS during-flood image for the best MI value, which has been translated to the left, and up by certain pixels and rotated by certain angle. Figure 8 is the registered MODIS during-flood image, overlaid on the MODIS before-flood image.

The performance measure of the image registration has been evaluated and listed in Table 5. From this table, we can observe that before registration when the before- and during-flood images are evaluated along with the RMSE and PFE are not optimal in comparison with that of registered image using nature-inspired techniques. The parameter values used for the nature-inspired techniques to align the during-flood image are the same as discussed earlier.

5.3. Comparison of nature-inspired techniques

Since the problem is non-deterministic polynomial-time hard, nature-inspired techniques can be an effective alternative to solve such problems and try to find optimal or near-optimal solutions for real-world problems (Glover and Kochenberger 2003). In recent

Table 4. Optimal MI value using MODIS image (before and during flood).

Parameter	MI for MODIS image (before and during flood)	GA	PSO	FA
(t_x, t_y)	(0,0)	(−48, −30)	(−49, −28)	(−49, –30)
θ	0	4	5	5
Max MI	0.2297	0.3223	0.3464	0.3985

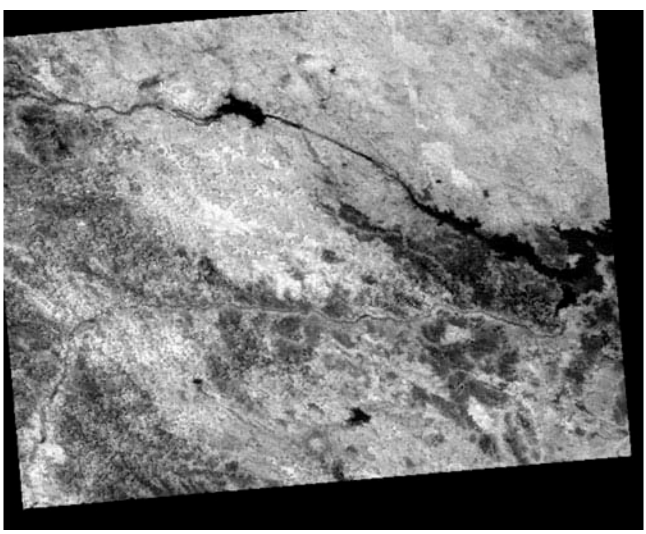

Figure 7. Registered MODIS (during flood) image.

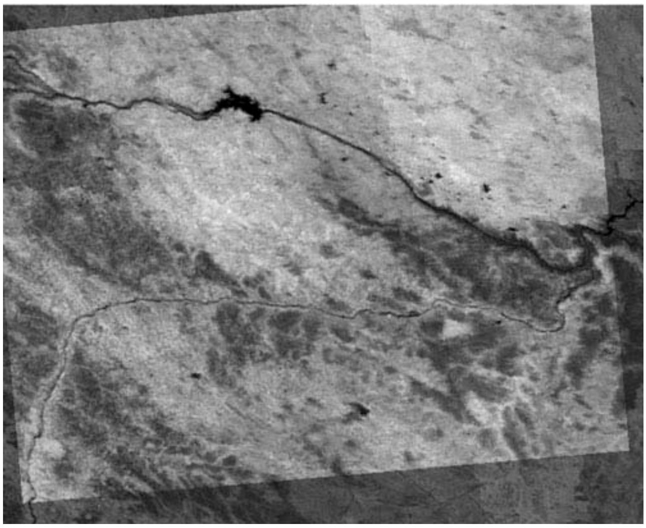

Figure 8. Registered MODIS (during flood) image is overlaid on the MODIS (before flood) image.

Table 5. Performance evaluation of nature-inspired technique using MODIS image (before and during flood).

Performance measures	MODIS before-flood image with ground truth	MODIS during-flood image with ground truth	Registered image			
			SA (Press *et al.* 1994)	GA	PSO	FA
MI	–	–	0.1979	0.3223	0.3464	0.3985
RMSE	0.315	0.302	0.2987	0.1449	0.1404	0.1113
PFE	0.3645	0.3407	0.2325	0.0568	0.0438	0.0252
Time (s)	–	–	11.356	106.262	82.411	85.521

years, many nature-inspired techniques have been used to solve image registration-related problems (Talbi and Batouche 2004, Wachowiak *et al.* 2004, Senthilnath *et al.* 2012a, 2013b).

From Tables 1 and 4, we can observe that the results obtained using GA and PSO are not optimal in comparison with that of FA. Since image registration has been formulated as a continuous optimisation problem, the translation and rotation picked by the population at each iteration may not be optimal, due to the perturbation of the agents within its limit. Therefore, results obtained by GA and PSO are not optimal. On the other hand, FA provides us with optimal results as the search space is effectively scanned by each firefly with its neighbouring firefly for finding the optimal fitness value which can be seen clearly in Figures 9 and 10. Similarly, from Tables 3 and 6, we can observe that the mean value after 20 independent runs, both PSO and FA are closer to the optimal MI value as their searching capability is consistent, and they perform better than GA in terms of fitness.

Conventionally, the SA (Press *et al.* 1994) is widely used for MI-based image registration (Maes *et al.* 1999, Bernon *et al.* 2001). The SA is compared with nature-

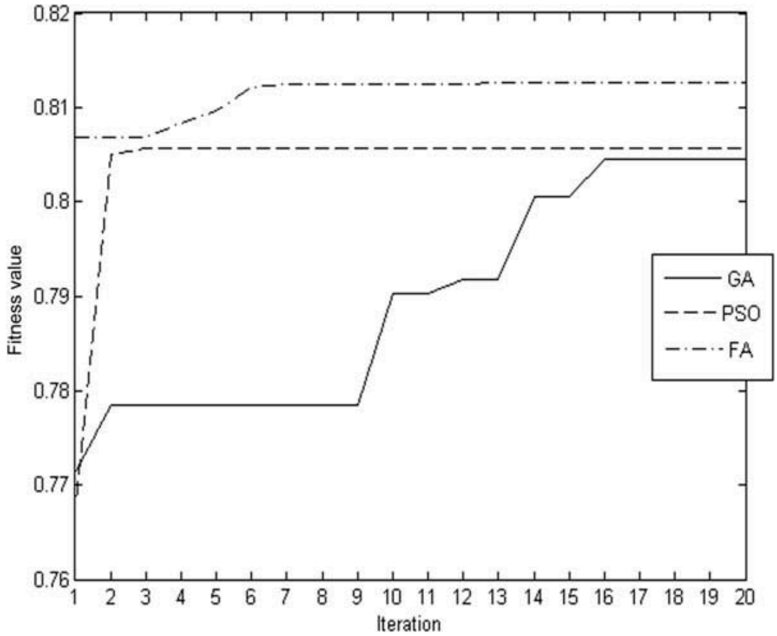

Figure 9. Variation of MI with each iteration for the LISS III and SAR images.

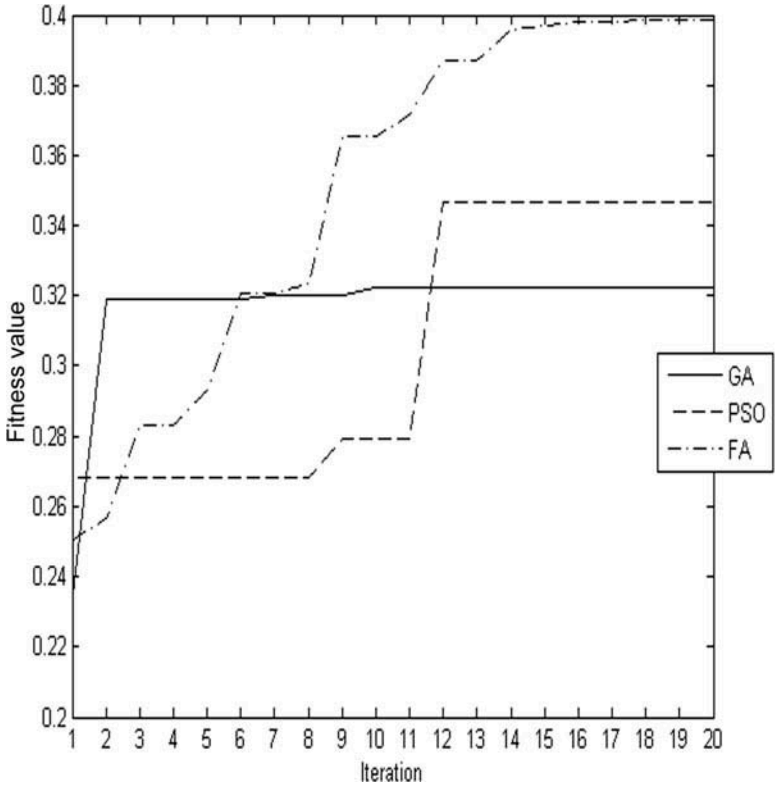

Figure 10. Variation of MI with each iteration for the MODIS images.

Table 6. Results of nature-inspired techniques after 20 runs using MODIS image (before and during flood).

Nature-inspired techniques	Optimal	Worst	Mean	Standard deviation
GA	0.3223	0.2728	0.2951	0.0753
PSO	0.3464	0.3139	0.3318	0.0326
FA	0.3985	0.3841	0.3891	0.0129

inspired methods as shown in Tables 2 and 5. From these tables, we can observe that the MI values of nature-inspired methods are better than that of SA. This is due to SA is prone to local optima, unlike nature-inspired methods, which converge to a global optimum.

The results obtained by the performance measures for the image registration techniques are listed in Tables 2 and 5. As seen in Table 2, the empirical evaluation procedure provided a RMSE of about 0.4131 for PSO and FA, in comparison with a RMSE value of 0.4418 for GA. For a good registration, the RMSE value should be closer to zero. Similarly, the PFE is zero when the registered image and the ground truth image fit exactly. From Table 2, we can observe that FA has the smallest PFE of 0.1605, whereas PSO has a PFE of 0.1663 and GA a PFE of 0.1996.Additionally, in comparison with nature-inspired methods (GA, PSO and FA), SA (Press *et al.* 1994) has higher RMSE and PFE values of 0.8165 and 0.4407, respectively. Hence, the nature-inspired methods show a better performance in finding optimal MI values for efficient image registration. Similarly, RMSE and PFE values for nature-inspired techniques in multi-temporal MODIS image registration can be seen in Table 5.

The experiments were conducted on Intel (R) Core (TM) i7 CPU with 4 GB RAM, and Windows XP system using Matlab 7.6. From Tables 2 and 5, we can observe that the CPU time for convergence is short for conventional optimisation method such as the SA. The computation time of SA is low in comparison with that of the nature-inspired methods. This is because nature-inspired methods are population-based, and the convergence of the population forms the optimal solution. Among the nature-inspired techniques, the convergence time of PSO and FA is fast in comparison with that of GA.

The convergence plots (Figures 9 and 10) show us the rate of convergence of the different algorithms; out of 20 runs, we selected the one which has converged to the optimal value. We can see that both PSO and FA converge very quickly compared with GA. In Figure 9, the GA fitness value increases with each passing iteration and then stabilises at a constant value of 0.8044 from the 16th iteration onwards. Although PSO has converged faster within three iterations, the value 0.8057 is not optimal in comparison with that of FA. Compared with all the nature-inspired techniques, FA has converged to optimal solution in 12 iterations and stabilises at a constant value 0.8126.The fitness variations of nature-inspired techniques can be observed in Figure 10 for the multi-temporal MODIS image registration.

6. Conclusions

In this article, we have presented a population-based approach for automatically registering multi-temporal satellite images using the key concept of MI. This MI value has been optimised using nature-inspired techniques (GA, PSO and FA), instead of calculating the MI for all possible angles of rotation and translation. Thus, nature-inspired approaches can speed up the process. In our experiments, we have observed that FA proved to be a better technique to find the maximum MI for better image registration. The performance of these registration methods are evaluated using quality measures. The empirical evaluations of quality measures indicate that although the images are from different sensors, the maximisation of MI can still be a valid metric to measure the degree of match between the images.

From this study, it has been observed that for registering the during-flood image with the before-flood image, all the nature-inspired techniques can achieve better solutions in terms of higher MI compared with conventional method. FA can achieve the best results among all the three techniques. This has demonstrated the effectiveness of our proposed approach.

Although the results are very promising, there is still room for improvements. For example, the variations of image sizes and processing of images with noise may provide opportunities for further research. In addition, images with incomplete parts are challenging for image registration. It will be useful to investigate these topics further.

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