

# IMAGE TO MAP REGISTRATION BASED ON META-HEURISTIC ALGORITHMS

Farhad Samadzadegan<sup>1</sup>, Ghasem Abdi<sup>\*2</sup> and Seyed Hossein Seyed Pourazar<sup>3</sup>

<sup>1</sup>Professor, Department of Geomatics Engineering, University College of Engineering, University of Tehran, Tehran, Iran; Tel: + 98-21-88986851;  
E-mail: samadz@ut.ac.ir

<sup>2</sup>Graduate student, Department of Geomatics Engineering, University College of Engineering, University of Tehran, Tehran, Iran; Tel: + 98-21-88986851;  
E-mail: ghasem.abdi@ut.ac.ir

<sup>3</sup>Graduate student, Department of Geomatics Engineering, University College of Engineering, University of Tehran, Tehran, Iran; Tel: + 98-21-88986851;  
E-mail: h.pourazar@ut.ac.ir

**KEY WORDS:** Bees Algorithm, Cat Swarm Optimization Algorithm, Genetic Algorithm, Image Registration, Meta-heuristic Algorithms.

**ABSTRACT:** Image registration problem in computer vision and remote sensing can be established via solving an optimization problem as the best pattern of match points is desired. This paper, introduces novel methods for automatic image registration with respect to image-to-object spaces based on key features consideration. The present approaches are designed to be completely independent from the sensor type and any prior information on the exterior orientation. Moreover, in the proposed procedures, Genetic Algorithm (GA), Bees Algorithm (BA), and Cat Swarm Optimization Algorithm (CSO) are used to match the corresponding features and fit the satellite image on the digital vector map by optimizing the transformation accuracy on checked and control points. Theoretical concepts and experimental results of three strategies are presented. Inspecting the results, it is concluded that three developed algorithms have the potential to find match point patterns correctly and more effectively and efficiently in comparison with conventional methods. Comparative evaluation of the results also specifies that for this particular purpose, BA performs more effectively and efficiently.

## 1. Introduction

The automatic registration of image data is a key task in computer vision and remote sensing. Although remarkable progress has been achieved in integrating GPS and inertial data to directly georeference airborne or spaceborne imagery, the use of corresponding primitives in object and image space in the framework of an aerial triangulation will not become obsolete. Even though high accuracy can be achieved by direct georeferencing, the use of ground control will always be mandatory for system calibration or accuracy control (Hild, Haala, & Fritsch, 2000). Meta-heuristics make few or no assumptions about the problem being optimized and can search very large spaces of candidate solutions. They are used for combinatorial optimization in which an optimal solution is sought over a discrete search-space and the search-space of candidate solutions grows exponentially as the size of the problem increases which makes an exhaustive search for the optimal solution infeasible (Blum & Roli, 2003). In this paper, GA, BA, and CSO are used to match the corresponding features and fit the satellite image on the digital vector map by optimizing the transformation accuracy on checked and control points.

## 2. Basic Concept of Image Registration

Successful exploitation of the high accuracy potential of satellite imageries depends on the ability of the mathematical models for the sensor modelling. Mathematical modelling approaches for orientation and registration of different satellite imageries have been investigated by many research groups (Madani, 1999; Tao & Y. Hu, 2001; Grodecki, 2001). A feature-based image registration method requires reliable feature extraction and feature matching procedure to robustly estimate the best registration transformation parameters (Meshoul & Batouche, 2008). The presented formulations for image registration conceptually can be divided into two main groups: Rigorous Sensor Models (RSMs) and Generic Sensor Models (GSMs) (Samadzadegan, Hahn, & Hosseini, 2003). RSMs reconstruct the spatial relations between remotely sensed imagery and the ground scene based on conventional colinearity equations. As RSMs basically are nonlinear models, the linearization and the need for pre-estimation of the initial values of the unknowns are inevitable (Samadzadegan et al., 2003). Nevertheless, most of high resolution satellite vendors do not intend to present their sensor ephemeris data. There is consequently a need for a range of alternative practical approaches in the conditions that we could not easily apply the RSMs. Consequently GSMs have been

adopted a decade ago as a sophisticated solution for overcoming the RSMs limitation (PADERES, 1989; Greve, Molander, & Gordon, 1992). GSMs are commonly based on mathematical models, e.g. Rational functions, Direct Linear Transformation (DLT), Projective and Affine models. More about affine, 3D Affine Transformation is a first order expansion of polynomials:

$$\begin{aligned}x &= a_1.X + a_2.Y + a_3.Z + a_4 \\y &= b_1.X + b_2.Y + b_3.Z + b_4\end{aligned}\tag{1}$$

where  $x, y$  are coordinates of points in original image,  $X, Y, Z$  are coordinates of points in digital vector map, and  $a_1, a_2, a_3, a_4, b_1, b_2, b_3, b_4$  are affine parameters.

### 3. Matching of Conjugate Points Based on GA

Using integer string encoding scheme for chromosome string, the validity of conjugate points is encoded. Each gene presents a point id and each chromosome presents a potential solution for point matching problem based on input and output and length twice the number of candid match points ( $k$ ). The first  $k$  columns of each chromosome devoted to points of the master image and the rest refer to the corresponding common points in the slave image. Since each point has only one match, the applied technique should be capable of selecting the points uniquely. Some initial parameters need to be set for the algorithm such as population size ( $N$ ), crossover probability ( $P_C$ ), mutation probability ( $P_M$ ), and number of elite ( $N_E$ ), and the stopping criterion for the loop ( $N_G$ ).

The work flow of feature based matching based on GA is as below (Samadzadegan, Saeedi, & Hoseini, 2006):

- 1) A set of chromosomes are randomly generated as initial population ( $N$ ).
- 2) While (The termination condition is to stop the GA search procedure after the algorithm converges to same result)
- 3) The fitness computation process is carried out for each chromosome by calculating the STD value achieved for the mapping function which is considered to be affine transformation (Equation. 1).
- 4) This step is involved with the producing of the next generation:
  - 4.1) For individual selection,  $N_s$  individuals are selected based on roulette selection (Samadzadegan et al., 2006).
  - 4.2) The mating is then performed randomly based on crossover probability using the crossover operation. The crossover used in this research is the uniform crossover.
  - 4.3) Using the mutation probability, each selected individual is mutated by randomly altering one bit in the chromosome string. The position of the bit to be altered is also randomly selected. In order to favour the discovery of good solutions, we use the concept of elitism in the developed algorithm. Accordingly, a number of best solutions ( $N_E$ ) in each iteration are transferred directly to the next generation without taking part in selection, crossover or mutation stages.
- 5) End While.

### 4. Matching of Conjugate Points Based on BA

In proposed BA based image registration method, each bee represents a potential solution for image registration problem based on input and output image points and each site represents the candidate conjugate points pattern. In this case, each bee represents an array sized twice the number of candid matching points ( $k$ ). The first  $k$  columns devoted to points of the master image and the rest refer to the points in the slave image to represent different sites for searching match points. Since each point has only one match, the applied technique should be capable of selecting the points uniquely. The algorithm requires some parameters to be set, namely: number of scout bee ( $n$ ), number of sites selected for neighborhood searching ( $m$ ), number of top-rated (elite) sites among  $m$  selected sites ( $e$ ), number of bees recruited for the best  $e$  sites ( $n_{ep}$ ), number of bees recruited for the other ( $m_e$ ) selected sites ( $n_{sp}$ ), and the stopping criterion for the loop ( $N$ ).

The work flow of feature based matching based on BA is as below (Pham, Otri, Afify, Mahmuddin, & Al-Jabbouli, 2007):

- 1) A set of scout bees population ( $n$ ) are randomly selected to define the  $k$  pairs of conjugate points.
- 2) The fitness computation process is carried out for each site visited by a bee, calculating the STD value achieved for the mapping function which is considered to be affine transformation (Equation. 1).
- 3) While (The termination condition is to stop the BA search procedure after the algorithm converges to same result)
- 4) In this step, the  $m$  sites with the highest fitnesses are designated as "selected sites" and chosen for neighborhood search. Then, the algorithm conducts searches around the selected sites, assigning more bees to search in the vicinity of the best  $e$  sites. Selection of the best sites can be made directly according to the fitnesses associated with them. Alternatively, the fitness values are used to determine the probability of the sites being selected. Searches in the neighborhood of the best  $e$  sites – those which represent the most promising solutions - are made more detailed. As already mentioned, this is done by recruiting more bees for the best  $e$  sites than for the other selected sites. Together with scouting, this differential recruitment is a key operation of the BA. In this paper, Because of discrete nature of

problem, neighbourhood search is changed as follows: Selected dimensions are replaced with random id.

5) For each patch, only the bee that has found the site with the highest fitness (the “fittest” bee in the patch) will be selected to form part of the next bee population. In nature, there is no such a restriction. This restriction is introduced here to reduce the number of points to be explored.

6) In this step, the remaining bees in the population are assigned randomly around the search space to scout for new potential solutions. At the end of each iteration, the colony will have two parts to its new population: representatives from the selected patches, and scout bees assigned to conduct random searches.

7) End While.

## 5. Matching of Conjugate Points Based on CSO

In proposed CSO based image registration method, each cat represents a potential solution for image registration problem based on input and output image points and each site represents the candidate conjugate points pattern. In this case, each cat represents an array sized twice the number of candid matching points (k). The first k columns devoted to points of the master image and the rest refer to the points in the slave image to represent different sites for searching match points. Since each point has only one match, the applied technique should be capable of selecting the points uniquely. The algorithm requires some parameters to be set, namely: number of cat (n), a mixture ratio (MR) of joining seeking mode together with tracing mode, Seeking Memory Pool (SMP), Seeking Range of the selected Dimension (SRD), Counts of Dimension to Change (CDC), and Self-Position Considering (SPC), a constant ( $c_1$ ) and the stopping criterion for the loop (N).

The work flow of feature based matching based on CSO is as below (Chu, Tsai, & Pan, 2006):

- 1) A set of cats population (n) are randomly selected to define the k pairs of conjugate points.
- 2) The fitness computation process is carried out for each site visited by a cat, calculating the STD value achieved for the mapping function which is considered to be affine transformation (Equation. 1).
- 3) While (The termination condition is to stop the CSO search procedure after the algorithm converges to same result)
- 4) Then haphazardly pick number of cats and set them into tracing mode according to MR, and the others set into seeking mode.
  - 4.1) For each cat of “seeking” sub-set apply seeking mode.
  - 4.2) For each cat of “tracing” sub-set apply tracing mode.
- 5) End While.

### 5.1. Seeking Mode

This sub-model is used to model the situation of the cat, which is resting, looking around and seeking the next position to move to. The work flow of seeking mode is as below (Chu et al., 2006):

- 1) Make j copies of the present position of cat k, where  $j = \text{SMP}$ . If the value of SPC is true, let  $j = (\text{SMP} - 1)$ , then retain the present position as one of the candidates.
- 2) For each copy, according to CDC, randomly plus or minus SRD percents of the present values and replace the old ones. In this paper, Because of discrete nature of problem, this step is changed as follows: Selected dimensions are replaced with random id.
- 3) Calculate the fitness values (FS) of all candidate points.
- 4) If all FS are not exactly equal, calculate the selecting probability of each candidate point by (Equation. 2); otherwise set all the selecting probability of each candidate point be 1.
- 5) Randomly pick the point to move to from the candidate points, and replace the position of cat k.

$$P_i = \frac{|FS_i - FS_{\max}|}{|FS_{\max} - FS_{\min}|} \quad (2)$$

where  $FS_b = FS_{\max}$ .

### 5.2 Tracing Mode

Tracing mode is the sub-model for modeling the case of the cat in tracing some targets (Chu et al., 2006). The action of tracing mode can be described as follows (Chu et al., 2006; Xu, Wang, & J. Hu, 2008):

- 1) Update the velocities according to (Equation. 3).
- 2) Check if the velocities are in the range of maximum velocity. In case the new velocity is over-range, it is set equal to the limit.
- 3) Update the position of cat k according to (Equation. 4).

$$v_k = v_k \circ (r_1 c_1 \otimes (x_{\text{best}} \ominus x_k)) \quad (3)$$

where  $x_{\text{best}}$  is The position of the cat, who has the best fitness value,  $x_k$  is The position of cat k,  $c_1$  is a constant, and  $r_1$

is a random value in the range of [0, 1].

$$x_k = x_k \oplus v_k \quad (3)$$

The operators applied in this section are described in (Xu et al., 2008).

## 6. Experiments and Results

The potential of the proposed methods is evaluated using IRS-P5 imagery and corresponding digital map which covered almost mountainous region. In the first step 40 points were extracted in the image and 50 points in the digital map by applying a modified Moravec operator. Figure. 1 shows the distribution of the extracted points in image and digital map.

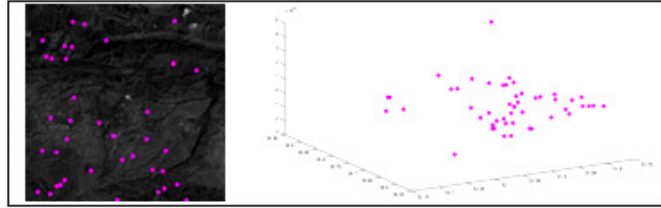


Figure 1: Extracted image points.

Proposed methods are applied to find optimum pattern of match points via extracted points in images of the dataset. To evaluate the capability of the proposed methods in matching the conjugate points, three different levels of experiment were implemented. At the first level 10 pairs of conjugate points are searched using developed algorithms. 3D affine transform (Equation. 1) is considered as mapping model between two images. To inspect the robustness of the proposed methods in terms of different number of conjugate points, the methods are tested considering increased number of points in two levels of 20 and 30 pairs of points. Initial parameters chosen for GA, BA, and CSO are presented in (Table 1). The stopping criterion is set as non-development in last 100 iterations.

Table 1. a: Initial Parameter for GA, b: Initial Parameter for BA, and c: Initial Parameter for CSO.

a		b		c	
GA Parameters	Value	BA Parameters	Value	CSO Parameters	Value
N	200	N	50	n	50
$N_E$	10	M	25	MR	10
$P_C$	0.6	E	10	SMP	20
$P_M$	0.1	$N_{ep}$	100	CDC	2
		$N_{sp}$	25	SPC	1
				$C_1$	0.5

In the Figure 1, Figure 2, Figure 3 and Figure 4 are found 10, 20 and 30 pairs of match points respectively. To have a better perception over the performance of each algorithm, convergence diagrams of each one in all three levels of experiment are also presented.

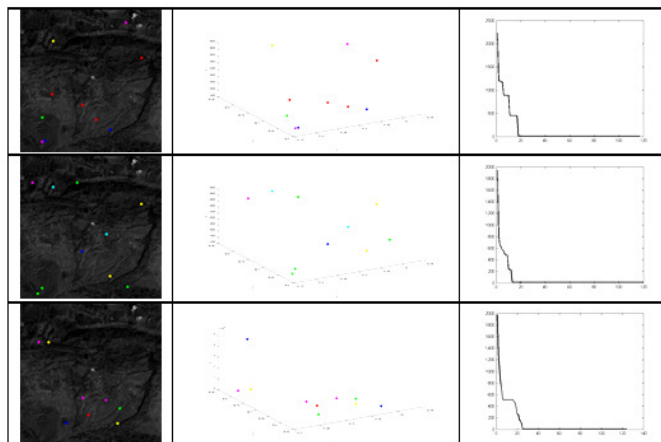


Figure 2: GA (above), BA (middle), and CSO (below) results, 10 pairs of match points.

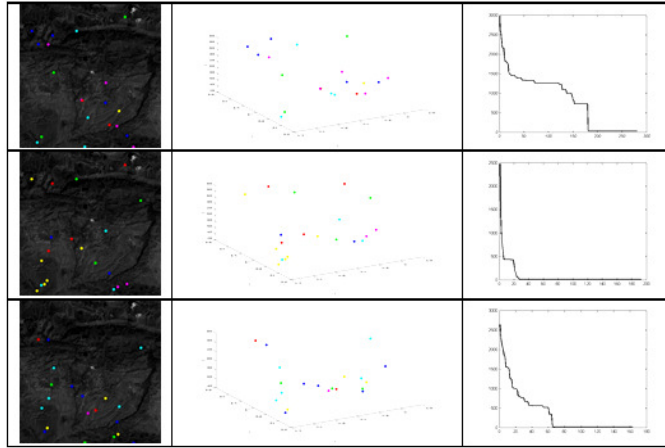


Figure 3: GA (above), BA (middle), and CSO (below) results, 20 pairs of match points.

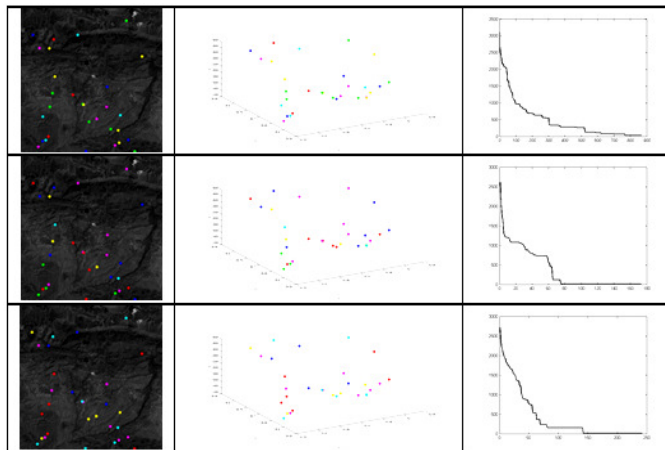


Figure 4: GA (above), BA (middle), and CSO (below) results, 30 pairs of match points.

As it can be perceived from the (Figure 2, Figure 3 and Figure 4), proposed methods have the potential of finding correct pattern of conjugate points in all levels of the experiment which are inspecting 10, 20 and 30 pairs of match points.

A comparative view over the performances of three algorithms is accessible by having a look over the convergence diagrams of three methods. First of all it is clear that GA and CSO achieve convergence in almost larger number of iterations in comparison with BA. Besides trends of GA and CSO convergence diagrams reveals that it sometimes traps in local optimums for a number of iterations. While BA convergence diagrams show a smoother trend of convergence. This limitation in GA and CSO behavior might be the consequence of initial parameters which points to its sensitivity to the determination of parameters.

## 7. Conclusions

In this study potential of GA, BA, and CSO were inspected in solving point matching problem and image registration. Three algorithms were evaluated matching different numbers of conjugate points and results were presented.

Inspecting the results, it is concluded that three developed algorithms have the potential to find match point patterns correctly and more effectively and efficiently in comparison with conventional methods. It was also emerged that the developed BA shows higher performance than GA and CSO in terms of number of iterations. Besides, based on the experiments, it can be declared that Genetic and CSOs are more sensitive to the determination of initial parameters. Further attempts can be conducted to investigate the role of initial parameters of BA and evaluation the algorithm in solving 3D image registration problem.

## References

- Blum, C., & Roli, A., 2003. Metaheuristics in combinatorial optimization: Overview and conceptual comparison. *ACM Computing Surveys (CSUR)*, 35(3), 268–308.
- Chu, S. C., Tsai, P., & Pan, J. S. 2006. Cat swarm optimization. *PRICAI 2006: Trends in Artificial Intelligence*, 854–858.
- Greve, C. W., Molander, C. W., & Gordon, D. K., 1992. Image processing on open systems. *Photogrammetric engineering and remote sensing*, 58(1), 85–89.
- Grodecki, J., 2001. Ikonos stereo feature extraction–RPC approach. In *Proc. ASPRS Annual Conference*, St. Louis (pp. 23–27).
- Hild, H., Haala, N., & Fritsch, D., 2000. A strategy for automatic image to map registration.
- Madani, M., 1999. Real-time sensor-independent positioning by rational functions. In *Proceedings of ISPRS Workshop on Direct Versus Indirect Methods of Sensor Orientation* (pp. 25–26).
- Meshoul, S., & Batouche, M., 2008. Aligning images with multiple objectives. In *Evolutionary Computation, 2008. CEC 2008.(IEEE World Congress on Computational Intelligence). IEEE Congress on* (pp. 2067–2072).
- PADERES, F., 1989. Batch and on-line evaluation of stereo SPOT imagery. In *1989 ASPRS/ACSM Annual Convention*, Baltimore, MD; UNITED STATES (pp. 31–40).
- Pham, D. T., Otri, S., Afify, A., Mahmuddin, M., & Al-Jabbouli, H., 2007. Data clustering using the bees algorithm. In *40th CIRP International Manufacturing Systems Seminar*.
- Samadzadegan, F., Hahn, M., & Hosseini, M., 2003. Aria: Automatic registration of images based on artificial intelligent techniques. In *Proceedings ISPRS Workshop on Challenges in Geospatial Analysis, Integration and Visualization II*.
- Samadzadegan, F., Saeedi, S., & Hoseini, M., 2006. Automatic Image to Map Registration Based on Genetic Algorithm. *WSEAS Transactions on Signal Processing*, 74–79.
- Tao, C. V., & Hu, Y., 2001. A comprehensive study of the rational function model for photogrammetric processing. *PE & RS- Photogrammetric Engineering & Remote Sensing*, 67(12), 1347–1357.
- Xu, Y., Wang, Q., & Hu, J., 2008. An Improved Discrete Particle Swarm Optimization Based on Cooperative Swarms. In *2008 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology* (pp. 79–82).