An Improved Binary Particle Swarm Optimization of RFM's for ALSAT2 Imagery

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Abstract
Rational function model (RFM) is commonly used in photogrammetric and remote sensing applications because it does not need sensor parameters. Therefore, the RFM terms or also rational polynomial coefficients (RPCs) have no physical significance but depends on many ground control points (GCPs) that make the model prone to the over parameterization problem. This paper proposes a new binary particle swarm optimization algorithm to surmount the issue of over-parameterization and find the optimum combination of RPCs for the RFM by adding a new transfer function in binary PSO in order to increase the convergence speed and avoid the local minimum phenomenon. The results showed that the proposed method is compatible with different types of RFM, more stable, and gives higher accuracy than the traditional binary PSO.

Keywords
Rational function model, particle swarm optimization, Ortho-rectification, meta-heuristic, high-resolution satellite images.

1. Introduction

One of the most important sources of geographic information systems (GIS) is high-resolution satellite imagery. The high-resolution satellite images are actually used in several contexts at both the industrial and scientific domain [1] but raw images usually contain some significant geometrical distortions. This distortion depends on the device (airplane or satellite), type of sensor, and the overall field of view, which cannot use the raw images directly in GIS without ortho-rectification in order to correct the geometrical deformations that were introduced during acquisition [2]. Ortho-rectification is the method of transforming an image's central projection into an orthogonal, uniform-scaled view. Thus, the distorting effects of tilt optical projection and terrain relief are removed [3]. The high accuracy potential of ortho-rectification depends on the relationship between images and object spaces [4]. For that, there have been functions and mathematical models developed either through empirical models (such as 2D/3D polynomial or 3D rational functions, RFs) or with rigorous (physical) models [2]. The rigorous models mostly based on the collinear-equation are lack generality because they are complex and its imaging model can differ from one sensor type to another. In addition, parameters such as orbital satellite ephemeris, attitudes, and the physical parameters of the sensor should also be provided for geo-positioning based on a rigorous sensor model; but those parameters may not be accessible because they expose satellite and sensor core technology. Protecting certain key parameters IKONOS, QuickBird and other commercial satellite imagery vendors have adopted empirical models, simpler and more general imaging platform the renowned type and mainly used in empirical models is rational function model (RFM) [3]. There are two methods to solving the RFM named as dependent-terrain and independent-terrain. In the case of the independent terrain, RFM is solved by using the physical sensor model; otherwise in the absence of the sensor parameters,

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the RFM is solved by using a set of ground control points (GCPs). This solution depending on the number and the distribution of the ground control point on the terrain is known as dependent-terrain method [5]. The independent-terrain approach, RFM necessitates a large number of accurate, well-distributed GCPs which is a time-consuming and costly process. In addition, RFM coefficients or also rational polynomial coefficients (RPC) have no physical significance which makes it difficult to find their best combination [6]. To overcome these problems the binary form of meta-heuristic algorithms can be helpful in optimization and determining the optimum RPCs.

Recently, many investigations carried out on the employment of the meta-heuristic approaches for RFM optimizations. Genetic algorithms (GAs) and particle swarm optimization (PSO) are the most useful technique in the literature employed to find the optimum number and combination of RFM parameters. GA-based approaches for RFM optimization were introduced in [7], [8]. Zoej et al in [7] used GA to find an optimum RPC by recommending a three-category division of ground points (GPs): Ground check points (GCPs) are used to estimate RPCs; dependent check points (DCPs) are used to estimate cost functions; and independent check points (ICPs) are used to measure the accuracy of the optimum RFM obtained by the method. In [8] a modified version of GA was employed for RFM optimization. Jennati in [8] have suggested using qualified genes in chromosome body to create some genetically modified (transgenic) chromosomes. The conventional PSO and its modified version, known as PSO for rational function optimization (PSORFO), were introduced in [6] and [9] respectively. PSORFO was the first PSO-based approach presented in the RFM literature, that used binary particles to decide whether or not the RPCs where present in the RFM structure and designed to be more likely to omitting coefficients rather than maintaining them. Yavari have demonstrates that the binary modified PSO has outperformed GA in terms of computational time and accuracy [6], [9]. Thereafter, PSO's employment has been the subject of several research works as in [10-11].

This paper presents a binary version of PSO (BPSO) to RFM optimization applied for the Algerian satellite (ALSAT2) imagery ortho-rectification. The rest of the paper is organized as follows briefly description of the RFM is presented in section II, the related work presented in section III, implementation and the results are provided in section IV, in section V we described our proposed algorithm, Finally, we give our conclusions in section IV.

2. Theoretical background

2.1. Rational function model RFM

RFM is composed of two mathematical equations which define the spatial relationship between ground space (X,Y,Z) and image space (r,c) using a ratio polynomial [12] as follows :

$$\mathrm{r} = \frac{\mathrm{P_1(X,Y,Z)}}{\mathrm{P_2(X,Y,Z)}}\ , \tag{1}$$

$$\mathrm{c} = \frac{\mathrm{P_3(X,Y,Z)}}{\mathrm{P_4(X,Y,Z)}}, \tag{2}$$

Where:

$$\begin{aligned}\mathrm{P_i} = {} & \mathrm{a_{i,0} + a_{i,1}X + a_{i,2}Y + a_{i,3}Z + a_{i,4}XY + a_{i,5}XZ + a_{i,6}YZ + a_{i,7}X^2 + a_{i,8}Y^2 + a_{i,9}Z^2} \\ & \mathrm{+ a_{i,10}XYZ + a_{i,11}X^3 + a_{i,12}XY^2 + a_{i,13}XZ^2 + a_{i,14}X^2Y + a_{i,15}X^3} \\ & \mathrm{+ a_{i,16}YZ^2 + a_{i,17}X^2Z + a_{i,18}Y^2Z + a_{i,19}Z^3,}\end{aligned} \tag{3}$$

Unknown RFCs can be solved with the linearized RFM form [13], [14] as in the following

$$\mathrm{P_1(X,Y,Z) - rP_2(X,Y,Z) = 0}\ , \tag{4}$$

$$\mathrm{P_3(X,Y,Z) - cP_4(X,Y,Z) = 0}\ , \tag{5}$$

The above equations can then be written as follows, by using n GCPs [12]:

$$y = Ax + e \,, \tag{6}$$

Where :
A: design matrix
y: observations vector
e: residuals vector
x: vector of RPCs.

The least-squares (LS) method can be applied to determine RPCs as follows:

$$x = (A^T A)^{-1} A^T y \,, \tag{7}$$

2.2. Particle Swarm Optimization for RFM optimization

Particle swarm optimization is one of the most common meta-heuristic optimization algorithms inspired by social intelligence and cooperative behavior displayed by various species to fill their needs in the search space. The first version of the particle swarm algorithm developed by James Kennedy and Russell Eberhart in 1995 which work in continuous search space [15], [16].

In RFM optimization, the binary form is applied. The standard binary PSO can be defined by the following equations [15]:

$$v_{ij}(t+1) = w.v_{ij}(t) + c_1 r_1 \left(p_{ij}(t) - x_{ij}(t)\right) + c_2 r_2 \left(p_{gj}(t) - x_{ij}(t)\right) \,, \tag{8}$$

Where :
- t is the iteration number.
- v_{ij} is the velocity of the bit j of i[th] particle bounded within a range of [v_{min},v_{max}],
- x_{ij} is the position of the bit j of i[th] particle.
- P_g denotes the best particle of the swarm, that is the particle with the best objective function value, and The best previous position of the i[th] particle in its own searching trajectory is recorded and represented as Pi.
-W is the inertia weight.

The update function for the position is defined as follows:

$$x_{ij}(t+1) = \begin{cases} 1, & \text{if } r_{ij} < \emptyset(v_{ij}) \\ 0, & \text{otherwise} \end{cases} \,, \tag{9}$$

Each element in the vector velocity is regarded as the input of a normalizing function (transfer function) and usually is a sigmoid function [17] which determines the probability in the range of [0,1].

3. The proposed binary PSO for RFM optimization (BPSO-RFO)

The algorithm begins with a population of particles which is a set of RFMs structure generated at the first run randomly in a string of the binary values. This implies that each particle is a combination of one and zero, indicating the presence or absence of the corresponding coefficient RPC in the RFM. In this work, the RFM with 78 parameters was used; hence each particle is represented by a string of 78 binary values as indicated in figure bellow.

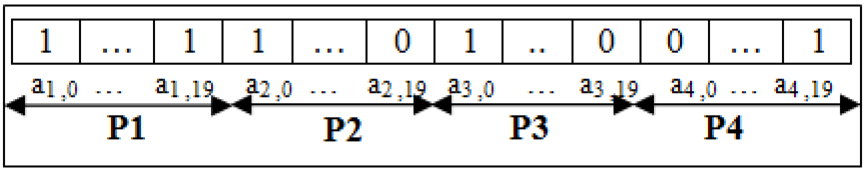


Figure 1: Particle representation

RFM optimization aims to minimize the number of terms and maintains sufficient accuracies therefore the normalizing function should be structured to be more likely to omit, rather than maintain the terms. Hence in our algorithm called BPSO-RFO the *tanh* function is used as the normalizing function due it deliver successful results as it demonstrated in [9], so the bits updating is performed with eq.9 using the velocity of the bit calculated by eq.8, the normalizing function formula is as follows:

$$\emptyset(v_{ij}) = \begin{cases} \tanh(v_{ij}), & \text{if } v_{ij} > 0 \\ 0, & \text{otherwise} \end{cases} , \quad (10)$$

The algorithm is repeatedly updated until a criterion for termination is reached. In this study, we declared the maximum number of iterations (t_{max}) to be termination condition. Fig.2 illustrates the flowchart of our proposed algorithm BPSO-RFO.

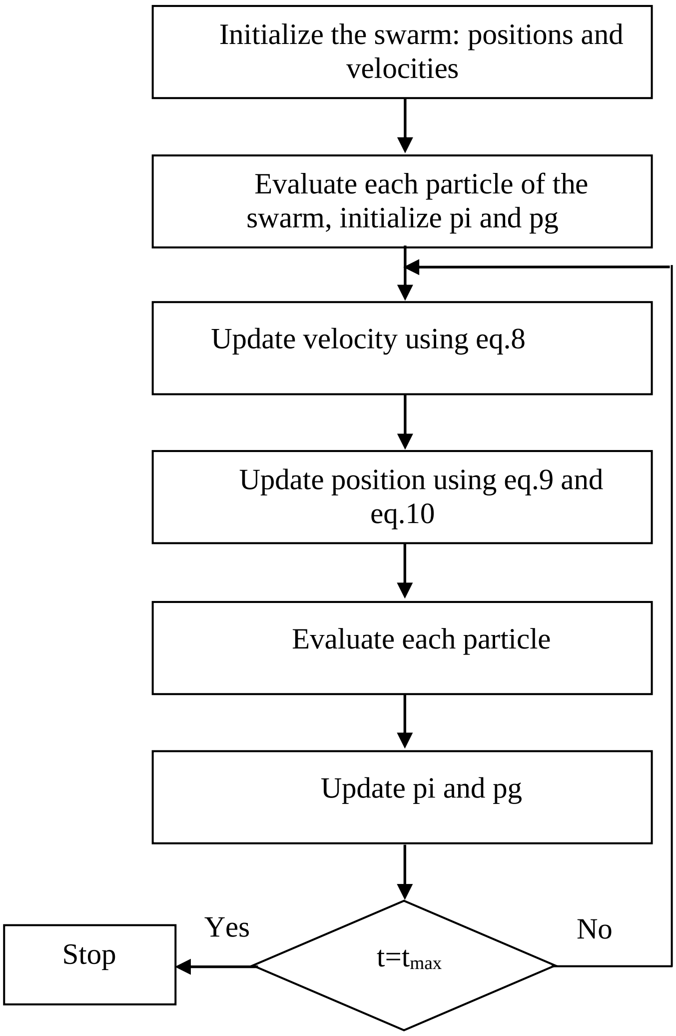
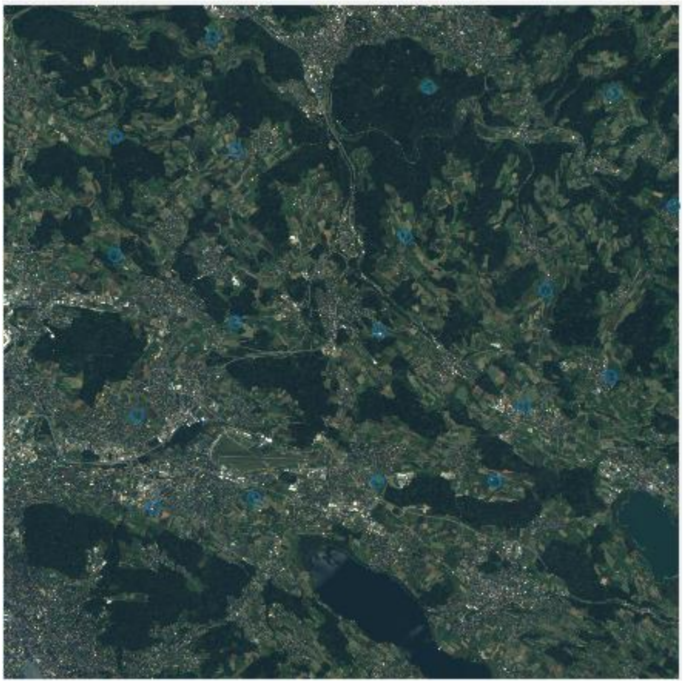


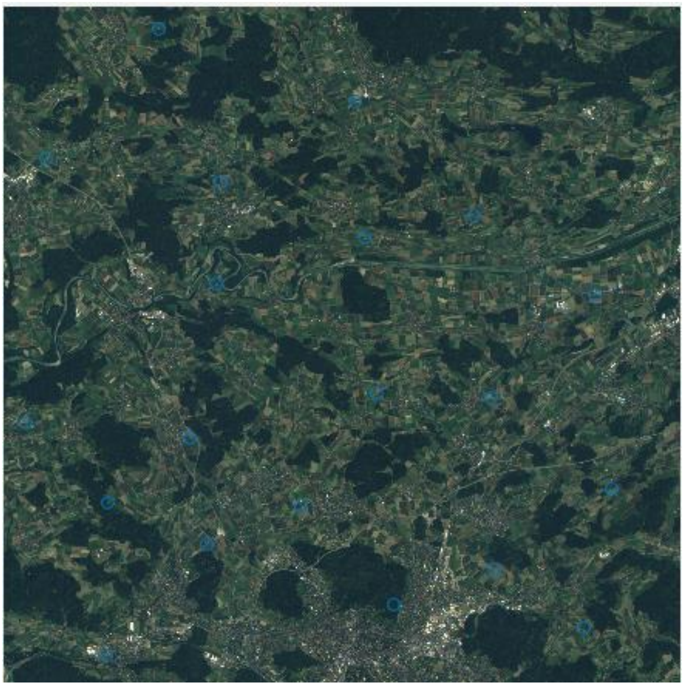
Figure 2: The flowchart of BPSO-RFO

4. Implementation and methodology

Two high-resolution images were used for the test, these images acquired by the Algerian satellite ALSAT2 over Winterthur city, Switzerland. The first one “Winterthur_ 1” consists of 18 control points (CPs) and the second “Winterthur_ 2” contains 20 control points (CPs). These CPs detected directly from terrain when the measurements were realized in August 2007 dicted in the report site of test and validation by [19]. Fig.3 shows Winterthur images of the satellite ALSAT2 within their CPs location.



(a) Winterthur_1 image



(b) Winterthur_2 image

Figure 3: The ALSAT2 test images.

The RFM optimization process is applied under the CPs in three different parts. First part of these points is employed to estimate the unknown coefficients of the model, which is called Ground Control Points (GCPs). The second part of CPs is used to calculate the fitness value for each particle named Dependent Checkpoints (DCPs). And the last part of these points is used just for accuracy assessment that is addressed as independent check points (ICPs).

Generally, the most common measure used is Root Mean Square Error (RMSE) given by this equation

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2}{N}}, \tag{11}$$

Where:
N is the total number of points, (x_i, y_i) the estimated coordinate (x, y), $(\hat{x}_i, \hat{y}_i)$ denote the actual coordinate (x, y).

We can summarize our methodology of RFM optimization based on the proposed algorithm as follow:

1. Estimation of the RPCs proposed by each particle by using a set of GCPs and the least square method (LS).
2. Evaluation of each particle by calculating the RMSE over DCPs which is the cost function.
3. Updating the RFM structure according to the BPSO-RFO algorithm.

The experiments have been implemented using MATLAB on a personal computer with a 2.40GHz Intel Core i3 CPU and an 8 Gb RAM. Table 1 mentions the parameters of the proposed method.

Table 1
Parameters used of the BPSO-RFO algorithm

Population size		30
v	**v_{max}**	+3
	v_{min}	-3
w		0.7
t_{max}		200
C1		1.5
C2		1.5

5. Results and Discussion

To evaluate the performance of the proposed algorithm BPSO-RFO, different testing experiments are carried out by selecting different combinations of well distributed GCP/ICP. In all experiments a 20% of the GCPs were selected randomly as DCP to calculate the cost function of each particle. In such issues, the RMSE over DCPs was widely used as a cost function. The accuracy of the obtained results is determined by two measuring criteria: first the RMSE which is calculated over ICPs, second the standard deviation (STD). STD is a proper indicator of stability since it is measured over RMSEs.

Furthermore, a comparison was conducted with the conventional binary PSO and standard GA with the same combinations of GCPs/ICPs. The genetic operators crossover and mutation probabilities used in the experiment are respectively 0.75 and 0.001.

As the meta-heuristic algorithms given a different result in each execution, each algorithm is executed 10 times; the better one with the lowest cost function was selected as the best and mentioned in table 2.

The experiments have been divided into two sections: the first is a comparison between our algorithm (BPSO-RFO) to the conventional PSO and GA in terms of accuracy, stability and convergence speed; the second experiment is about the effect of the number of RPCs on the accuracy of our algorithm.

Table 2
The accuracy and stability results of different algorithms

Data set	GCP/ICP	RMSE over ICP			STD		
		BPSO-RFO	Conventional PSO	Conventional GA	BPSO-RFO	Conventional PSO	Conventional GA
Winterthur _1	15/3	0.8726	0.9836	**0.8287**	**0.2435**	0.3304	1.6440
	12/6	**0.8839**	1.1383	2.9475	**1.0130**	1.4216	204.4333
	10/8	**1.1363**	4.4652	298.4170	**0.6519**	2.0883e+03	1.0112e+03
	08/10	**1.6471**	205.3063	133.8651	**0.4785**	9.4025	2.7009e+04
	07/11	**1.8783**	175.7524	126.6041	**1.4996e+03**	9.3179e+03	1.7138e+03
Winterthur _2	15/5	**0.8484**	0.8844	0.8781	**0.0822**	0.2578	2.9202
	12/8	**0.8827**	1.4710	0.8976	**1.0938**	2.9363	500.7724
	10/10	**1.2606**	17.0005	15.5123	**2.5304**	421.5296	372.7287
	08/12	**1.6258**	1.0265e+03	742.5804	**231.2884**	2.9080e+03	711.0490
	07/13	**1.9921**	1.0738e+03	780.0430	**126.8536**	2.4229e+03	4.0130e+03

5.1. The stability and accuracy analysis

As shown in Table 2 the BPSO-RFO achieve clearly better results than the conventional PSO in all cases and in most cases then the conventional GA in most cases either in term of accuracy or on stability, the value of RMSE over ICP shows the high accuracy of the proposed methods which can optimize the RFMs and obtain a sub-pixel on accuracy just with 12 GCPs. Through table 2, we observed that the BPSO-RFO achieved a sub-pixel if the number of GCPs is equal or superior to 12 points and if the number of GCPs is less than 10 the accuracy is degraded in the worst case to 1.99 pixels which is appropriate for photogrammetric and remote sensing applications.

Unlike the conventional PSO and GA, the accuracy value degraded to 1000 pixel this due to the stuck in local minima. In term of stability, our algorithm shows high stability also with 12 and 15 GCPs. In the overall view of the results our method is more stable than both conventional PSO and GA.

When comparing BPSO-RFO to the conventional PSO and GA, it is clear that BPSO-RFO is more accurate and stable, this due to the transfer function eq.10 which is designed to be more omit of the RPC than preserve them, this helped the BPSO-RFO to minimize the number of RPC to the minimum with acceptable accuracy.

5.2. Convergence speed analysis

To test the convergence speed of the literature methods, the best run among the 10 runs is selected in this section for convergence speed analysis. Fig.4 demonstrates the convergence curve of the literature methods with a different combinations of GCPs (15,12,7) for wientherthur1 and wientherthur2 data sets.

As observed in fig.4, the conventional PSO and GA have a slow convergence than BPSO-RFO which is much faster. Our algorithm shows significant performances due to the transfer function that does not just improve the accuracy but also the convergence speed.

5.3. The effect of the RPCs number analysis

To validate the effectiveness of the proposed method with different types of RFMs a comparative study is carried out by tested our algorithm for other RFMs with different number of RPC, so we chose the RFM of 18 terms (i.e., *P*1, *P*2, *P*3, and, *P*4: five, four, five, and four terms, respectively) and 42 terms (i.e., *P*1, *P*2, *P*3 and, *P*4: five, four, five, and four terms, respectively), the test is applied to Winterthur1 dataset with a different combination of GCPs (15,12,7). Table 3 shows the efficiency and compatibility of the proposed method with different types of RFM.

The best result provided with BPSO-RFO is with the RFM of 18 terms because their spaces search range is less than other RFMs (42 terms, 78 terms).

Table 3
The result of apply BPSO-RFO to different RFM types

GCP/ICP	RMSE over ICP		
	RFM with 18 terms	*RFM with 42 terms*	*RFM with 78 terms*
15/3	**0.8292**	0.8395	0.8726
12/6	**0.6568**	0.7858	0.8839
07/11	1.6922	**1.2126**	1.8783

6. Conclusion

This paper presents a modified binary PSO of RFM optimization for ALSAT2 images ortho-rectification. The proposed binary PSO can achieve a sub-pixel on accuracy with a very limited number of GCPs.

The results obtained demonstrate the performance of our proposed algorithm BPSO-RFO in term of accuracy and stability comparing to the conventional binary PSO and conventional binary GA in the most cases. In term of convergence speed the proposed binary PSO confirm its superiority to other tested method, the BPSO-RFO converges rapidly in most cases less than 60 iteration.

In the last test we apply the BPSO-RFO to different types of RFMs, the results show that the BPSO-RFO is compatible to any RFM types whatever the number of RPC, which make it a good application for RFM optimization.

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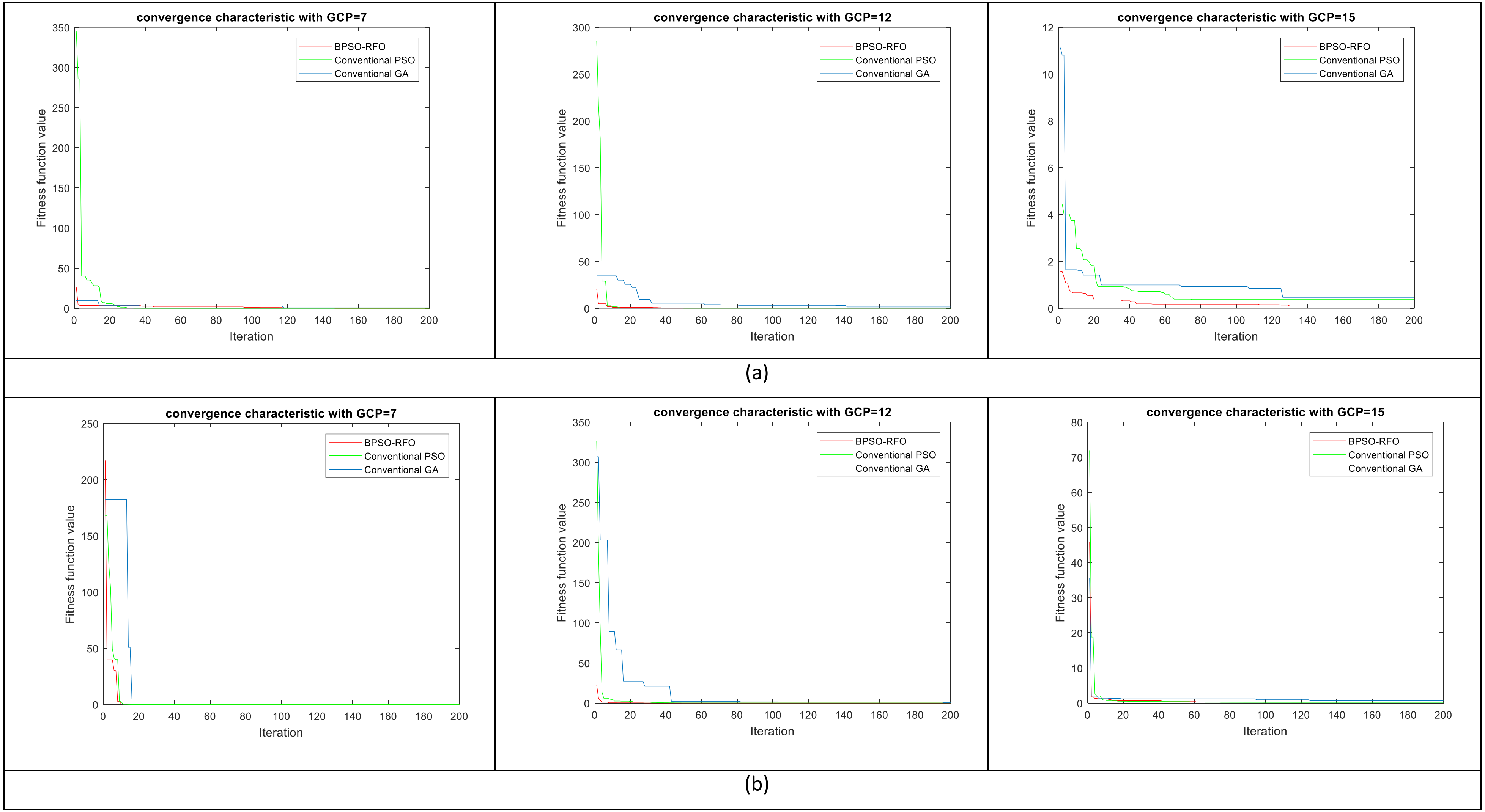

Figure 4: Convergence characteristic of the tested methods with different number of GCPs and different data set: (a) Winterthur_1 , (b) Winterthur_2