Using an Imperialistic Competitive Algorithm in Global Polynomials Optimization (Case Study: 2D Geometric Correction of IKONOS and SPOT Imagery)

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Abstract

The number of high resolution space imageries in photogrammetry and remote sensing society is growing fast. Although these images provide rich data, the lack of sensor calibration information and ephemeris data does not allow the users to apply precise physical models to establish the functional relationship between image space and object space. As an alternative solution, some generalized models such as global polynomials have been developed and used. This paper presents a hybrid method based on using imperialistic competitive algorithm (ICA) to find the best terms of global polynomials. The method was carried out for geometric correction of two different datasets, an IKONOS Geo-image and a SPOT image, with different number of ground control points (GCPs) and independent check points (ICPs). Results showed the success of achieving sub-pixel accuracies (0.2) for IKONOS and 2.5 pixels for SPOT image. The method was able to successfully handle over-optimization as it produces lower RMSEs compared to conventional approach. Also, the proposed method required much less time in comparison to other optimization algorithms like genetic algorithm (GA) and particle swarm optimization (PSO).

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1. Introduction

High resolution space imageries such as IKONOS and QuickBird have become very popular and useful in photogrammetry, remote sensing and civil applications. These images are often used for several purposes such as producing land cover maps, environmental monitoring and agricultural management (Hablb et al., 2007). To do these, the functional relationship between image space and object space must be established via sensor models which are typically classified as: Parametric (physical) models and Non-Parametric (generalized) models. Parametric models require the interior orientation and orbital parameters of the sensor to faithfully represent the geometry of the scene formation. These models are rigorous, proper for adjustment by analytical triangulation, and normally result in high modeling accuracy (Tao and Hu, 2001). The most popular one is the orbital parameter model which has been implemented by many authors for different tasks (Gugan, 1986; Fraser and Shao, 1996; Valadan Zoej and Petrie, 1998). On the other hand, Non-Parametric models use general mathematical functions (such as global polynomials) to make the mentioned relationship. These models do not require neither interior orientation parameters nor orbital ephemeris information and are therefore independent of sensor platforms and sensor types. Non-Parametric models are extensively dependent on the distribution of GCPs instead and hence very sensitive to the terrain topography, number of GCPs and their distribution (Baghani, 2012). Recently, some investigations have been conducted for these models (Tao and Hu, 2001, 2002; Dowman and Tao, 2002; Sadeghian and Delavar, 2003).

In many applications, due to the lack of sensor calibration information and the requirements for real time implementations, experts prefer to use non-parametric models for geometric correction of images and ignore the provided accuracy degradation (Tao and Hu, 2001). 2D global polynomials, 2D Projective and 2D Direct Linear Transformations are some examples of these models.

Term selection is the most important stage in using such models. In the conventional approach all terms are involved in the computational process which causes over-parameterization. To avoid this and find the most efficient terms, intelligent methods can be used, rather than trial and error which is highly time consuming and illogical.

Valadan Zoej et al. (2007) used genetic algorithm with different control parameter settings for rational functions optimization. The method was used for geometric correction of an IKONOS image with different number of GCPs. Results offered reduction of RMSE compared to conventional rational functions. Although, the presented algorithm was able to achieve sub-pixel accuracies, operational time of it was relatively high and not suitable for real time applications. Yavari et al. (2012) compared the particle swarm optimization and genetic algorithm for rational function models (RFMs) optimization. The methods were tested on an IKONOS Geo panchromatic image and also an image from Spot – 4 L1B. Although, the PSO algorithm was more efficient, the performance time of it was still high. Baghani (2012) used ant colony for RFMs optimization. The method was tested on a SPOT-L1A, SPOT-L1B and an IKONOS image in three different coordinates systems (CT, UTM and Geodetic). The thesis showed that the use of CT coordinate system yields higher accuracies in comparison to other two coordinate systems especially when few number of control points are used. The operational time for the method was considerably short with respect to similar algorithms like GA and PSO. Zhang et al. (2012) proposed a new RFM parameter optimization method based on scatter matrix and elimination transformation strategies. The method was tested on two data sets generated from SPOT-5 high-resolution sensor. Results showed that the precision of the method, with about 35 essential parameters, was 10% to 20% higher than that of the conventional model with all 78 parameters. But the terrain-dependent RFM was not considered in their work. Tengfei et al. (2014) proposed a method which first converts the problem of solving rational polynomial coefficients (RPCs) into a multiple linear regression and then implements nested regression to select optimal RPCs automatically. Different types of images, including QuickBird, SPOT-5, Landsat-5, and ALOS were involved in their test. The method performed better than conventional solution and gained a stable and reliable answer with less than 39 GCPs. Jannati and Valadan Zoej (2015) introduced genetic modification to speed up the basic GA for optimal term selection of RFMs. The method defined a qualification coefficient to examine qualification of individual genes. Two different case studies were used to evaluate the performance of the proposed algorithm. Results indicated that the method required less iterations such that speed was improved by 20 times, while the accuracies were preserved. It is seen that solving RPCs is a multicollinearity problem which is often solved by variable selection. Indeed, the original model is simplified by selecting a subset of variables from the original set which give the most significant response to the regression, and hence reducing multicollinearity.

This paper uses an imperialistic competitive algorithm to select the best terms of global polynomials and consequently gain a near optimum solution. The general equation of global polynomials is:

$$x = \sum_{i=0}^{n}\sum_{j=0}^{n} a_{ij}X^iY^j \quad (1)$$

$$y = \sum_{i=0}^{n}\sum_{j=0}^{n} b_{ij}X^iY^j \quad (2)$$

Where x and y are image coordinates, X and Y are ground coordinates and a_{ij} and b_{ij} are coefficients. Each term of the global polynomial models and removes a specific error of the image.

The reminder of this paper is organized as follows: Section 2 describes the solution method and proposed algorithm problem. The solution procedure and heuristic approaches are presented in Section 3. Section 4 presents computational experiments and discussions. Section 5 includes concluding remarks and future researches.

2. The solution method and proposed algorithm (ICA)

The imperialist competitive algorithm is a new evolutionary algorithm that was introduced by Atashpaz and Lucas (2007). Like any evolutionary algorithm, it starts with a random initial population and by creating supervised-random solutions it tries to attain more optimum results. The basic difference between ICA and other evolutionary algorithms is that instead of a natural or human base it uses a socio-political evolution process (i.e. imperialism).

ICA begins with an initial population in which each individual is called a country. Some of the best countries (here solutions with minimum RMSE) in the population will be selected as imperialist and the other countries will be the colonies of this imperialists (regarding to the imperialist's fitness). A set of one imperialist and its colonies is called an empire. After the formation of initial empires, as a procedure of imperialism, the colonies start to move toward their imperialist country, which causes improvements in socio-political aspects of colonies (e.g., culture, language and etc.). This means that the fitness of solutions related to the colonies will improve. The procedure of moving colonies toward imperialists is called assimilation. Sometimes it may cause a colony to become the imperialist of the related empire. As another natural procedure of imperialism, sometimes revolutions happen that cause sudden and unpredictable changes in colonies and as a result it may cause the colony become more powerful (this procedure expand the solution space and prevents the algorithm from sticking in a local optimum). After applying these procedures the total power of each empire is calculated. Any empire tries to get the possession of the colonies of other empires. The power of each empire depends on both the power of its imperialist country added to a percentage of mean power of its colonies. After the computation of empires power, the weakest colony in the weakest empire will be the possession of one of the empires depending on their power. This procedure goes on until the stop a criterion is satisfied (usually when there is only one empire that possesses the whole world and the imperialist of this empire is our desired solution). Fig. 1 shows the flowchart of ICA.

3. Implementing ICA for best terms selection

3.1 Initial population

In this research the initial population includes N solutions that each one is a (1 × n) binary vector representing a random selection of terms we would like to use for the polynomial and 'n' is the number of terms we want to use. For instance, the solution vector shown in Fig. 2 implies that terms 1, 3, 6, 8 and 11 are selected from terms 1-15. Therefore, the desired polynomials are:

$$x = a_0 + a_2Y + a_5y^2 + a_7xy^2 + a_{10}x^3y \quad (3)$$

$$y = b_0 + b_2Y + b_5y^2 + b_7xy^2 + b_{10}x^3y \quad (4)$$

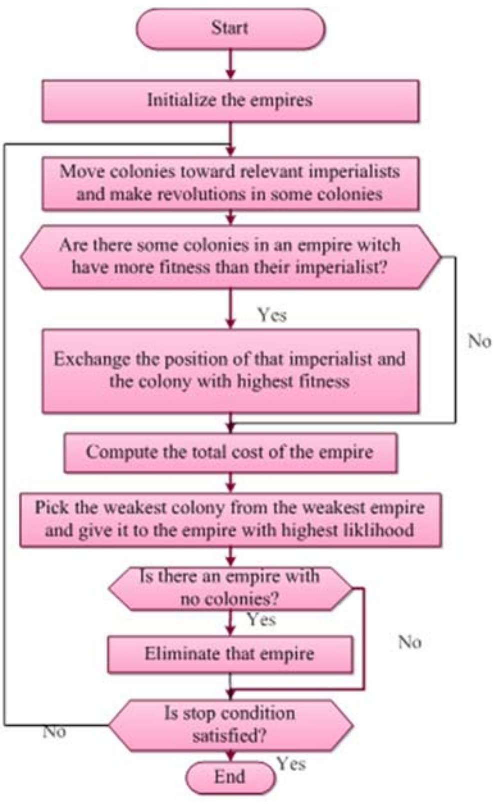

Fig. 1: The flowchart of ICA

3.2 Generating the empires

After the initial population is formed the fitness of each solution is computed. Then some of the solutions with better fitness (i.e., lowest RMSE) are selected as imperialists (N_{imp}) and the reminder of solutions will be the colonies of this imperialists ($N_{col} = N_{pop} - N_{imp}$). Here and in Section 3.4 we have used the procedure applied by Moradi and Zandieh (2013). To distribute the colonies between imperialists proportionally, first we calculate the N_{imp} using related parameter (here PR) by N_{imp} = round (PR* N_{pop}) then, normalized cost of nth imperialist is defined as:

$$\text{Normcost (i)} = C_{max} - C_i \quad i = 1, 2, \ldots, N_{imp} \qquad (5)$$

Where C_i the cost of nth imperialist and C_{max} is the maximum cost in the population. Then the normalized power of each empire is defined by:

$$P_i = \frac{Normcost\ (i)}{\sum_i^{N_{imp}} Normcost\ (i)} \quad i = 1, 2, \ldots, N_{imp} \qquad (6)$$

Thus the initial number of colonies of nth imperialist is about

$$Size(i) = round\ (\boldsymbol{P_i} * N_{col}) \quad i = 1, 2, \ldots, N_{imp} \qquad (7)$$

Hence stronger imperialists have more colonies while weaker ones have less. After defining the Size(i) for each imperialist, related number of colonies are chosen randomly from N_{col} and assigned to them.

3.3 The assimilation and revolution policy

After the initial empires are formed, the colonies in each empire move toward their relevant imperialists. Considering the characteristics of our problem, the following procedure is used for assimilation (Nourmohammadi et al., 2013)

1) Calculate the assimilation rate (AR) that depicts the percentage of similarity between the imperialist and the colony.
2) Consider the vector of an imperialist and a colony.
3) Generate a 1 × n vector of random numbers with uniform distribution from (0, 1).
4) Compare each value of the random vector to AR. If the value is lower than AR change the related value in colony vector to the related value in imperialist vector (see Fig. 3).

The revolution policy is somehow similar to mutation operators in GA by which the value of some element in solution vector randomly will be exchanged (see Fig. 4). In any iteration, a rate of colonies will revolt against their imperialists that may cause a colony to overcome its imperialist and become the imperialist of related empire.

3.4 Empires evaluation, competition and elimination

As a natural process of imperialism, the empires try to take the possession of the colonies in other empires. In so doing this competition, the power of more powerful empires increases and the power of weaker ones decreases. The competition process is done by picking some (usually one) of the weakest colonies in the weakest empire and making a competition among all of the empires. The empires have the chance to take the possession of this colonies regarding to their power. The power of each empire is the power of its imperialist added to a percentage of mean power of its colonies which is shown by the following equations:

$$\boldsymbol{Pemp_i} = cost\ (\boldsymbol{imp_i}) + \alpha.\ mean\ (cost\ of\ colonies\ of\ the\ empire) \qquad (8)$$

Now the normalized power of each empire is defined by:

$$Norm\_\ \boldsymbol{Pemp_i} = \boldsymbol{max_i}\ (\boldsymbol{Pemp_i}) - \boldsymbol{Pemp_i} \qquad (9)$$

Thus the possession probability for each empire is defined by:

$$\boldsymbol{Pr_i} = \frac{\boldsymbol{Norm\_Pemp_i}}{\sum_i \boldsymbol{Norm\_Pemp_i}} \qquad (10)$$

Now the random vector R is formed in size of the number of empires with uniformly distributed numbers from (0, 1) and by simply subtracting Pr from R we have D = Pr – R. Now the mentioned colony (ies) is handed to an empire whose index D is maximum. In so doing this process, empires that remain with only their imperialist (empires with no colonies) will be eliminated. The algorithm will stop when the stop criteria is satisfied that's usually when only one empire remains and its imperialist is the best solution obtained.

4. Numerical results

Two different datasets were used for this research: an IKONOS Geo panchromatic image over central Hamedan city, and a SPOT image covering Isfahan, both in Iran. The IKONOS image was acquired on 7 October 2000 with 20.4 degree off-nadir angle and 47.4 degree sun elevation. The elevation within the study area ranged from 1700 to 1900 m. GCPs/ICPs for the test were extracted from NCC-produced digital maps, which employed a UTM projection on the WGS84 datum.

1	0	1	0	0	1	0	1	0	0	1	0	0	0	0

Fig. 2 : Example of a solution vector containing selected terms from 1-15

A colony vector	1	0	0	1	0	0
An imperialist vector	1	1	0	0	1	1
Random vector **(If AR = 0.5)**	0.523	0.321	0.724	0.841	0.229	0.912
New colony vector	1	1	0	1	1	0

Fig. 3: The assimilation policy

(Revolution policy)

1	0	0	0	1	1	1	0
	↓				↓		
1	1	0	0	1	0	1	0

Fig. 4: The revolution policy

The selected GCPs/ICPs in the imagery were distinct features (such as buildings and pools corners, and wall and roads crossings, etc.). The SPOT image but, is a Level 1A product acquired at June 1987 with 20.84 degree off- nadir angle. GCPs/ICPs of this data were measured using a dual frequency GPS system with sub-meter accuracy

Table 1: The RMSE values for two polynomials (15 and 21 terms) with two different combinations of GCPs and ICPs. RR= 0.1, P=0.1 and α=0.08, IKONOS imagery

		Hybrid approach (using ICA in GPs)				Conventional approach	
	Poly. terms	Pop. size	Aver. RMSE (m)	Min. RMSE (m)	Run Time (s)	RMSE (m)	Run Time (s)
27 GCPs and 47 ICPs	15	30	0.5115	0.5053	2.02	1.746	0.25
		40	0.5058	0.5053	4.92		
		50	0.5053	0.5053	7.7		
	21	60	0.5311	0.5053	8.65	2.112	0.40
		80	0.4967	0.4625	13.1		
		100	0.4911	0.4465	16.63		
35 GCPs and 39 ICPs	15	30	0.4460	0.4216	1.62	1.450	0.32
		40	0.4310	0.4216	5.34		
		50	0.4243	0.4216	6.3		
	21	60	0.2964	0.2756	9.22	1.986	0.53
		80	0.2826	0.2481	13.91		
		100	0.2811	0.2391	17.87		

Table 2: The RMSE values for two polynomials (15 and 21 terms) with two different combinations of GCPs and ICPs. RR= 0.1, P=0.1 and α=0.08, SPOT imagery

			Hybrid approach (using ICA in GPs)			Conventional approach	
	Poly. terms	Pop. size	Aver. RMSE (m)	Min. RMSE (m)	Run Time (s)	RMSE (m)	Run Time (s)
18 GCPs and 17 ICPs	15	30	30.893	30.426	1.31	45.782	0.17
		40	30.686	29.586	3.05		
		50	30.320	29.586	6.14		
	21	60	28.691	26.437	10.95	48.623	0.26
		80	27.472	25.562	14.65		
		100	27.620	25.562	18.37		
25 GCPs and 10 ICPs	15	30	29.980	29.199	2.97	41.053	0.21
		40	29.167	28.317	5.45		
		50	29.167	28.317	7.87		
	21	60	26.654	24.949	11.63	46.744	0.33
		80	26.599	25.837	17.37		
		100	26.819	25.837	18.84		

The elevation within the study area ranged from 528 to 1147 m. Figure 5 shows the distribution of GCPs/ICPs of both datasets.

Two different set of GCPs/ICPs were fed through the ICAs with different parameter settings. Tables 1-2 represent the result for each image. In these tables, the first column shows the combination of GCPs/ICPs that was used. The next column is for the number of terms of polynomials that are involved in the optimization process. The third column represents the population size of the algorithm and the 4th and 5th column are average and minimum values of RMSE for 10 runs of algorithm respectively. The 6th column is the average required time of the algorithm to give the stated results. The last two columns are devoted to RMSE and Run Time of the conventional approach respectively. The parameters PR, P and α respectively denote the percentage of imperialists in each population, the percentage of revolution in empires and the percentage of mean power of colonies related to an empire in calculating its power.

The algorithms were implemented in Matlab R2010b on a PC with a Duo CPU 2.40 GHz with 4GB of RAM. The most efficient results by the hybrid approach offers 0.2391m and 24.949m RMSE for IKONOS and SPOT data respectively. It is apparent that the proposed method results in lower RMSEs than conventional approach (i.e. handling over-parameterization), but requires more time instead. Increasing the number of GCPs gives more redundancy in equations and hence will decrease RMSEs as it is expected. But, increasing population size doesn't make meaningful and practical changes in RMSEs, and even takes more time which makes this choice worthless as a way to gain better accuracies. Instead, it will be much more effective to use higher terms of polynomials.

The selected terms of global polynomials were not exactly the same for each image, but as a general view, the frequency of each term to be chosen in 120 tests is shown in figure 6.

The IKONOS data has been tested by PSO and GA in Yavari et al. (2012). The population size of GA was 50 and that of PSO was 30. The paper has tested different combinations of GCPs/ICPs which we use the one with 35 GCPs and 39 ICPs. A relative comparison of reported results proves the high efficiency of ICA in terms of both calculated RMSE and the required time. The values of PSO and GA for RMSE were 0.62m and 0.60m respectively while ICA achieved 0.44m and 0.42m with Pop. Sizes of 50 and 30 respectively. The required time of ICA is averagely 673 times less than GA and 1158 times less than PSO. Table 3 shows a summary of comparing ICA, GA and PSO results on the IKONOS data.

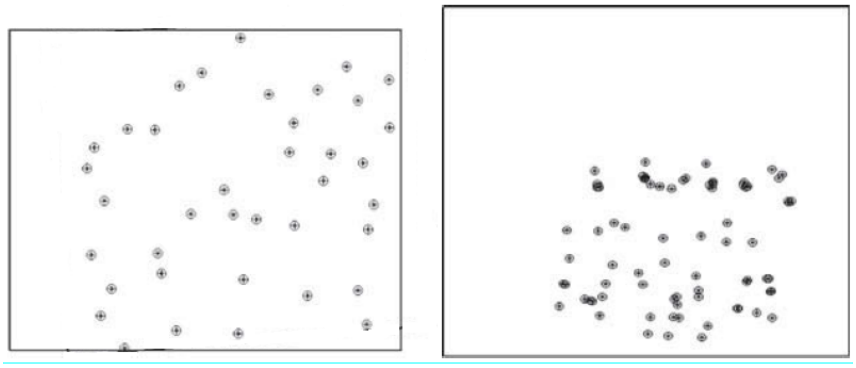

Fig. 5: Distribution of GCPs/ICPs: (a) SPOT image, (b) IKONOS-Geo Image

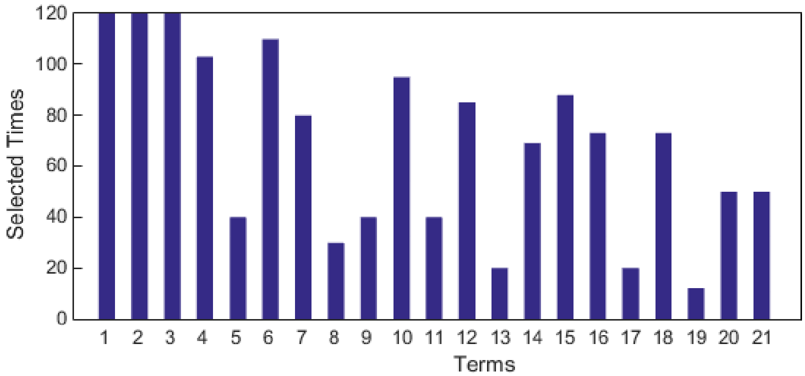

Fig. 6 : The frequency of each term to be chosen in 120 tests of the algorithm on both datasets

Table 3: The summary of comparing the results of GA, PSO and ICA, IKONOS data

Optimization algorithm	Number of GCPs and ICPs	Aver. RMSE in 10 runs (m)	Run time (s)
GA (Pop. Size = 50)	35 & 39	0.60	4240
ICA (Pop. Size = 50)	35 & 39	0.42	6.3
PSO (Pop. Size = 30)	35 & 39	0.62	1876
ICA (Pop. Size = 30)	35 & 39	0.44	1.62

5. Conclusions and future work

Due to the lack of sensor calibration and orbital parameters of high resolution imageries, non-parametric sensor models have become an attractive solution for photogrammetry and remote sensing experts. The main problem of such models is to find the best terms involved in the mathematical transformations. One of the most common non-parametric models is global polynomials. In this paper, Imperialistic Competitive Algorithm (ICA) has been used for determining the best terms of this model for geometric correction of an IKONOS and a SPOT image. Results showed the success of this method to overcome the over-parameterization problem regarded with conventional approaches (1-1.7m improvement in RMSE for IKONOS image and 20-25m for SPOT image). It is apparent that using more GCPs leads to better results, although their distribution must kept somehow uniform to ensure that the whole image has been covered. Results also suggest that increasing population size doesn't practically and meaningfully help to gain better accuracies while consuming more time. Implementing higher terms of polynomials would be a better choice to gain lower RMSEs. A relative comparison of the proposed method with GA and PSO proves its efficiency in terms of both calculated RMSEs and the required run time.

An interesting future research work may be the best selection of GCPs to be used besides the best selection of terms using evolutionary algorithms. This way, the process would be more automated and more optimized.

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