ISPRS Journal of Photogrammetry and Remote Sensing 139 (2018) 46–56

Contents lists available at ScienceDirect

ISPRS Journal of Photogrammetry and Remote Sensing

journal homepage: www.elsevier.com/locate/isprsjprs

An automatic optimum number of well-distributed ground control lines selection procedure based on genetic algorithm

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ARTICLE INFO

Article history:
Received 26 May 2017
Received in revised form 28 February 2018
Accepted 1 March 2018
Available online 4 April 2018

Keywords:
Genetic Algorithm (GA)
High Resolution Satellite Images (HRSIs)
Linear features
Optimum number of Well-Distributed ground control Information Selection (OWDIS)
Rational Function Model (RFM)
Registration

ABSTRACT

The procedure of selecting an optimum number and best distribution of ground control information is important in order to reach accurate and robust registration results. This paper proposes a new general procedure based on Genetic Algorithm (GA) which is applicable for all kinds of features (point, line, and areal features). However, linear features due to their unique characteristics are of interest in this investigation. This method is called Optimum number of Well-Distributed ground control Information Selection (OWDIS) procedure. Using this method, a population of binary chromosomes is randomly initialized. The ones indicate the presence of a pair of conjugate lines as a GCL and zeros specify the absence. The chromosome length is considered equal to the number of all conjugate lines. For each chromosome, the unknown parameters of a proper mathematical model can be calculated using the selected GCLs (ones in each chromosome). Then, a limited number of Check Points (CPs) are used to evaluate the Root Mean Square Error (RMSE) of each chromosome as its fitness value. The procedure continues until reaching a stopping criterion. The number and position of ones in the best chromosome indicate the selected GCLs among all conjugate lines. To evaluate the proposed method, a GeoEye and an Ikonos Images are used over different areas of Iran. Comparing the obtained results by the proposed method in a traditional RFM with conventional methods that use all conjugate lines as GCLs shows five times the accuracy improvement (pixel level accuracy) as well as the strength of the proposed method. To prevent an over-parametrization error in a traditional RFM due to the selection of a high number of improper correlated terms, an optimized line-based RFM is also proposed. The results show the superiority of the combination of the proposed OWDIS method with an optimized line-based RFM in terms of increasing the accuracy to better than 0.7 pixel, reliability, and reducing systematic errors. These results also demonstrate the high potential of linear features as reliable control features to reach sub-pixel accuracy in registration applications.

1. Introduction:

High Resolution Satellite Images (HRSIs) play an important role in the fields of photogrammetry and remote sensing (Poli and Toutin, 2012; Toth and Jóźków, 2016). To use HRSIs in different applications, these images should be registered to a well-known coordinate system using an appropriate mathematical model. The majority of registration methods can be done in four main steps: feature extraction, feature matching, transformation function estimation, and resampling (Brown, 1992; Goshtasby, 2005; Zitova and Flusser, 2003). Feature extraction and matching have been well studied (Bheda et al., 2014; Yavari et al., 2016). In addition, transformation function estimation is a crucial procedure to reach an accurate geo-referenced image to extract 3D spatial information.

The features used for registration are classified as point, linear and areal features. Point features are preferred more for registration purposes (Gianinetto and Scaioni, 2008; Valadan Zoej et al., 2006). Since 2000, the use of linear features in registration has increased. This is because of the reliability and ease of their extraction and matching procedures, as well as their abundance,

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https://doi.org/10.1016/j.isprsjprs.2018.03.002

particularly in urban areas (Habib and Kelley, 2001; Habib et al., 2004; Schenk, 2003; Yavari et al., 2016; Yavari et al., 2018). Therefore, this article is investigating the impact of the distribution of linear features as Ground Control Lines (GCLs) on accuracy improvement of the registration procedure. However, the proposed procedure is also applicable for other kinds of features such as Ground Control Points (GCPs).

From a photogrammetric point of view, mathematical models are categorized as either parametric or non-parametric models (Ahn et al., 2002; Boccardo et al., 2004; Chen et al., 2006; Crespi et al., 2010; Habib et al., 2007; Poli and Toutin, 2012; Toutin, 2006; Valadan Zoej and Sadeghian, 2003). Regarding linear features, many researchers present automatic registration methods based on parametric models (Akav et al., 2004; Habib and Kelley, 2001; Karjalainen et al., 2006; Liu et al., 2016; Marsetič et al., 2015; Mulawa and Mikhail, 1988; Schenk, 2003; Sheng and Zhang, 2017; Tommaselli and Lugnani, 1988; Tommaselli and Tozzi, 1996; Zhang et al., 2004). A detailed review of using linear features in collinearity equation and its advantages in comparison to coplanarity equation can be found in the work of Schenk (2003, 2004).

In addition to parametric models, some researchers attempt to use non-parametric models in registration purposes based on linear features. It can be due to the inaccessibility of orbital parameters and raw images of commercial HRSIs (Hu and Tao, 2002; Tao and Hu, 2001). For instance, the LBTM (Line-Based Transformation Model) is proposed by Shi and Shaker (2006) for image to image registration, though their method required at least one GCP to correct the translation parameters. Later, Li and Shi (2014) extended their work to Generalized Line-Based Iterative Transformation Model (GLBITM) by integrating the LBTM and generalized-point photogrammetry to eliminate the translation amount. Additionally, Wang et al. (2008) used linear features for automatic aerial image registration to a vector map, based on a 2D rigid transformation. Multi-temporal multi sensor image registration based on straight linear features is considered in Al-Ruzouq (2010). For this purpose, some extracted linear features are matched through Modified Iterative Hough Transform (MIHT). Simultaneously, an affine transformation is analyzed to determine the mathematical relationship between conjugate lines. Additionally, a similarity measure is derived to ensure the correspondence between conjugate lines. Zang et al. (2011) used straight linear features and MIHT to estimate the parameters of an affine transformation for UAV remote sensing imageries registration. In Zhao and Goshtasby (2016), linear features for registration of multi-temporal aerial images were used based on a 2D projective transformation.

Among different kinds of non-parametric models, the Rational Function Model (RFM) has some advantages (Hu and Tao, 2002; Tao and Hu, 2001), such as generality and independency on a geographic coordinate system, as well as sensor type. This is in addition to not requiring any initial information about the sensor parameters, such as ephemeris data and interior/exterior orientation parameters, applicability with partial images, and computational simplicity in conjunction with a fast execution time. In this regard, Lu et al. (2013) used Rational Polynomial Coefficients (RPCs) as the initial orientation parameters to perform an automatic vector map to HRSIs registration. Teo (2013) solved the traditional RFM as well as bias-compensation procedure using linear features similar to the work of Schenk (2003, 2004). The results showed that traditional line-based RFM could achieve pixel-level accuracy.

RFM can be solved using two methods (Tao and Hu, 2001). Terrain-independent, which uses the satellite parameters and sensor models with little or no ground control information for bias-compensation (Di et al., 2003; Dial and Grodecki, 2002; Fraser et al., 2006; Fraser and Hanley, 2003, 2005; Hu and Tao, 2002; Hu et al., 2004a,b; Qiao et al., 2010; Singh, 2008; Tong et al., 2010), and terrain-dependent, which uses only ground control information to compute the unknown parameters (Hu and Tao, 2002; Long et al., 2015; Tao and Hu, 2001; Tengfei et al., 2014; Valadan Zoej et al., 2006; Yavari et al., 2013). Constructing RFM using the terrain-independent method for geo-rectified images, such as Ikonos-Geo, is not feasible by end-users due to the inaccessibility of precise ancillary data (interior and exterior orientation parameters). Moreover, in old images, the RPCs may not be contained with HRSIs. Hence, the present paper only investigates the terrain-dependent direct forward RFM as a non-parametric model.

Since RFM terms do not have any physical meaning, they result in an additional error called over-parametrization error due to using a high number of inappropriate, correlated terms. Intrinsically, the design matrix also becomes rank deficient (Hu and Tao, 2002; Tao and Hu, 2001; Long et al., 2014, 2015; Yavari et al., 2013). The correlations between terms cause traditional procedure of finding the best arrangement of terms hardly feasible. Using improper order and combination of terms, along with an over-parameterization error increase the number of control information required to solve the unknown parameters as well as prevent the model for removing systematic errors. To cope with the mentioned shortcomings of a traditional RFM, a meta-heuristic method could be used to find optimum uncorrelated terms and a proper order of polynomials. In this regard, Yavari et al. (2018) proposed an Optimized Linear Feature-based RFM based on Particle Swarm Optimization (PSO) to find optimum uncorrelated terms. Considering the achieved results, the accuracy as well as the reliability of the proposed method improved significantly in comparison to a traditional line-based RFM.

Another major shortcoming of RFM as well as all non-parametric models is their sensitivity to the number, distribution, and accuracy of control information (Hu and Tao, 2002; Tao and Hu, 2001; Long et al., 2014; Yavari et al., 2013). These models fit a surface to the ground control information. Therefore, they are inherently interpolative and need a high number of well-distributed ground control information to reach a reliable accuracy (Hu and Tao, 2002; Tao and Hu, 2001). Hence, the necessity of using an optimum number of well-distributed ground control information still remains. It means that not all conjugate features are appropriate for solving the unknown parameters of a mathematical model. This could be due to the existence of correlations among features.

The impact of the number, accuracy and spatial pattern of point features (GCPs) is investigated in some articles (Mather, 1995; Sertel et al., 2007; Tao and Hu, 2001; Wang et al., 2005, 2012; Zhang et al., 2006; Zhou and Li, 2000). The manual selection of well-distributed GCPs has been studied previously in Tao and Hu (2001) and Mutluoglu et al. (2015). However, manually finding the best number and distribution of GCPs is a tedious work due to the high number of extracted and matched features in real datasets. For point features, Nguyen (2015) proposes an automatic process based on Genetic Algorithm (GA).

Similar to point features, the number and distribution of linear features as GCLs influence the accuracy and robustness of the registration results. Although, there is not any general automatic method to select optimum number and best distribution of GCLs. In these cases, using trial-and-error methods are not practical because of the high number of possible combinations. Moreover, zero-order optimization algorithms (Snyman, 2005) are regarded as the best alternatives. Among the zero-order optimization algorithms, GA (Haupt and Haupt, 2004; Sastry et al., 2005) and PSO (Hu et al., 2004a,b; Kennedy and Eberhart, 1995, 1997) are concerned as the most successful and frequently used optimization algorithms in different applications (Jannati and Valadan Zoej, 2015; Valadan Zoej et al., 2007; Yavari et al., 2012, 2013, 2018). Although, both GA and PSO could find approximately similar