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Parallel relative radiometric normalisation for remote sensing image mosaics

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A B S T R A C T

Relative radiometric normalisation (RRN) is a vital step to achieve radiometric consistency among remote sensing images. Geo-analysis over large areas often involves mosaicking massive remote sensing images. Hence RRN becomes a data-intensive and computing-intensive task. This study implements a parallel RNN method based on the iteratively re-weighted multivariate alteration detection (IR-MAD) transformation and orthogonal regression. To parallelise the method of IR-MAD and orthogonal regression, there are two key problems: the normalisation path determination and the task dependence on normalisation coefficients calculation. In this paper, the reference image and normalisation paths are determined based on the shortest distance algorithm to reduce normalisation error. Formulas of orthogonal regression are acquired considering the effect of the normalisation path to reduce the task dependence on the calculation of coefficients. A master-slave parallel mode is proposed to implement the parallel method, and a task queue and a process queue are used for task scheduling. Experiments show that the parallel RRN method provides good normalisation results and favourable parallel speed-up, efficiency and scalability, which indicate that the parallel method can handle large volumes of remote sensing images efficiently.

1. Introduction

In remote sensing applications, there is an increasing need to analyse remote sensing data over large areas, which involves mosaicking massive remote sensing images. Geo-analysis with remote sensing images is often conducted under the condition that the images are radiometrically consistent. As remote sensing images are acquired on different dates and different environmental or sensor conditions, relative radiometric normalisation (RRN) is routinely implemented to minimise radiometric differences among images. The RRN method applies one image as a reference and adjusts the radiometric properties of the subject images to match the reference image (Hall et al., 1991). Mosaicking a large area requires the processing of a number of adjacent images; thus the RRN process is a computing-intensive and time consuming task. In recent years, emerging parallel hardware architecture, such as computer clusters and multi-core processes, offers opportunity to enhance the performance of the processing of raster images (Valencia et al., 2007; Lee et al., 2011; Guan et al., 2012; Maulik and Sarkar, 2012; Van Den Bergh et al., 2012). To meet the demands of rapid radiometric normalisation of remote sensing images for mosaicking, it is necessary to implement RRN methods in parallel framework.

A few studies have been performed on the parallelisation of mosaicking (An et al., 2002; Wang et al., 2010; Chen et al., 2011; Wu et al., 2013). Most of them use histogram matching for radiometric normalisation because the process of histogram matching for each subject image is independent and can be easily parallelised. Although histogram matching is useful to match data of the same scene acquired on different dates with slightly different sun angles or atmospheric effects (Yang and Lo, 2000), it is not useful for assembling several images into a mosaic because they do not have common constant reflectance targets (Shimabukuro et al., 2002). Typically, the RRN methods used for mosaicking utilise a linear comparison of statistical characteristics of overlaps between adjacent images to derive gains and offsets from pseudo-invariant features (PIFs) (Hall et al., 1991; Du et al., 2002; Olthof et al., 2005; Paolini et al., 2006; Canty and Nielsen, 2008). Canty et al. (2004) demonstrated a successful example of mosaicking by automatically selecting invariant pixels between images using the multivariate alteration detection (MAD) technique (Nielsen et al., 1998). This mosaicking technique selects invariant pixels automatically except a decision threshold, and provides a favourable result with other manual methods (Schmidt

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et al., 2005; Schroeder et al., 2006). The method also uses orthogonal linear regression to perform the actual normalisation, which is preferred over the ordinary least squares regression. Canty and Nielsen (2008) introduced an iteratively re-weighted modification of MAD transformation (IR-MAD), which is superior to the ordinary MAD transformation in identifying significant change, particularly for data sets in which the fraction of invariant pixels is relatively small. To parallelise the method of IR-MAD and orthogonal linear regression, there is a “two-body problem”, which leads to the subject images to be normalised in order, to be solved. Based on the RRN method of IR-MAD and orthogonal linear regression, the “two-body problem” is analysed and corresponding solutions are suggested. The solutions include three procedures: determining the reference image, generating a tree composed of paths from subject images to the reference image and establishing formulas to calculate coefficients for each subject image with the least dependence. According to these solutions, the parallel scheme of RRN is proposed and the parallel method is implemented on specific parallel architecture with parallel techniques.

The rest of this paper is organised as follows. Section 2 introduces the RRN method of IR-MAD and orthogonal regression. Section 3 analyses the “two-body problem” in parallelising the method; and gives corresponding solutions and the parallel scheme. The performance experiments and analysis of the parallel method is discussed in Section 4. The last section gives the conclusion and the further study direction.

2. RRN using IR-MAD and orthogonal regression

The RRN method addresses two overlapping images: a reference image and a subject image. First, IR-MAD is performed to select invariant pixels from overlapping area. Then, orthogonal regression with the selected invariant pixels is employed to calculate normalisation coefficients for each band of the subject image. With normalisation coefficients, linear regression equations are set up, and finally normalised pixel intensities of the subject image are calculated using the equations.

2.1. IR-MAD for RRN

The IR-MAD method was first demonstrated by Canty and Nielsen (2008) for automatically selecting invariant pixels from the overlapping area of two adjacent images.

For two K band overlapping multispectral images, the pixel intensities in the overlapping area of the images are represented as F and G, respectively. F_i represents the intensities of the ith band of F, and G_i represents the intensities of the ith band of G. Consider the random variables U and V generated by any linear combinations of the spectral bands intensities as

$$\begin{aligned} U &= a^T F = a_1F_1 + a_2F_2 + \cdots + a_iF_i + \cdots + a_KF_K \\ V &= b^T G = b_1G_1 + b_2G_2 + \cdots + b_iG_i + \cdots + b_KG_K \end{aligned} \quad (i = 1 \ldots K) \tag{1}$$

The random variable created by the difference U–V combines change information into a single image. With suitable vectors a and b, the difference U–V can reveal the most changes, and the MAD variates are defined as

$$\mathrm{MAD}_i = U_{(K-i+1)} - V_{(K-i+1)} \quad (i = 1 \ldots K) \tag{2}$$

The vectors a and b can be calculated by standard canonical correlation analysis (CCA), to the F and G (Nielsen et al., 1998).

Let the random variable Z represent the sum of the squares of the standardised MAD variates:

$$Z = \sum_{i=1}^{K} \left(\frac{\mathrm{MAD}_i}{\sigma_{MAD_i}} \right)^2 \tag{3}$$

where σ_{MADi} is the variance of the no-change distribution.

$$\sigma^2_{MAD_i} = \mathrm{Var}(U_{K-i+1} - V_{K-i+1}) \quad (i = 1 \ldots K) \tag{4}$$

The no-change probabilities of observations can be defined as

$$\Pr(\text{no change}) = 1 - P_{\chi^2;K}(z) \tag{5}$$

The method described above is the process of MAD. In the IR-MAD method, the process of MAD iterates. The weights of all observation in the first iteration are one, and in the next iteration, the weights of observations are defined by the no-change probabilities. The entire process is iterated until some stopping criterion is met. The stopping criterion may be that there is little change in the canonical correlations or an iteration number is set. A threshold t is set and pixels that satisfy $\Pr(\text{no change}) > t$ are selected as the invariant pixels for regression.

2.2. Orthogonal regression

As mentioned above, the RRN method is developed under the assumption that the relationship between the intensities of invariant pixels in overlapping areas can be approximated by linear functions. Considering two overlapping multispectral images, each has K bands and N invariant pixels. One is selected as the reference, and the other is the subject image to be normalised. The formulation of orthogonal regression for RRN is

$$p_{ij}^{ref} - \varepsilon_{ij} = \alpha_i + \beta_i (p_{ij}^{sub} - \delta_{ij}) \quad (j = 1 \ldots N) \quad (i = 1 \ldots K) \tag{6}$$

where p_{ij}^{ref} is the intensity of the jth invariant pixel in the ith is band of the reference image, and p_{ij}^{sub} is the intensity of the jth invariant pixel in the ith band of the subject image. α_i and β_i are normalisation coefficients for the ith band in the subject image. ε_{ij} and δ_{ij} represent measurement errors of the intensities of the jth invariant pixel in the ith band of the reference image and the subject image. The estimator of α_i and β_i:

$$\begin{aligned} \hat{\beta}_i &= \frac{((s_i^{ref})^2 - (s_i^{sub})^2) + \sqrt{((s_i^{ref})^2 - (s_i^{sub})^2)^2 + 4s_i^2}}{2s_i} \\ \hat{\alpha}_i &= \overline{p_i^{ref}} - \hat{\beta}_i \overline{p_i^{sub}} \end{aligned} \tag{7}$$

with

$$\begin{aligned} (s_i^{sub})^2 &= \frac{1}{N} \sum_{j=1}^{N} (p_{ij}^{sub} - \overline{p_i^{sub}})^2 \\ (s_i^{ref})^2 &= \frac{1}{N} \sum_{j=1}^{N} (p_{ij}^{ref} - \overline{p_i^{ref}})^2 \\ s_i &= \frac{1}{N} \sum_{j=1}^{N} (p_{ij}^{sub} - \overline{p_i^{sub}})(p_{ij}^{ref} - \overline{p_i^{ref}}) \end{aligned} \tag{8}$$

where $\overline{p_i^{ref}}$ and $\overline{p_i^{sub}}$ are the means of the pixel intensities in the ith band of the reference image and the subject image.

3. Parallel implementation of RRN for mosaicking

3.1. The “two-body” problem

The “two-body” problem refers to the condition that RRN can only address a single pair of images at a time and that the normalisation coefficients of an image may be affected by those of other images. In a typical process of RRN for mosaicking, an