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GPU-accelerated large-size VHR images registration via coarse-to-fine matching

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ABSTRACT

This paper presents a coarse-to-fine large-size very high resolution image registration method. This method uses compute unified device architecture to speed up the acquisition of control points and image rectification. In coarse registration, the scale-invariant feature transform algorithm is used to match control points to estimate the initial global transformation parameters between images to be registered. The initial parameters are then used to guide Oriented FAST and Rotated BRIEF (ORB) feature matching in fine registration. To fix local distortion, image rectification is based on a linear mapping function computed from triangulations, and a self-adaptive scan filling algorithm is proposed to determine which triangle each pixel belongs to. Experiments are conducted with large-size satellite images. Results show that a graphics processing unit can obtain significant-acceleration factors while maintaining registration accuracy.

1. Introduction

Remote images registration is an essential task in image matching, change detection, quick response, and the construction of super-resolution images (Zitová and Flusser, 2003; Bentoutou et al., 2005; Xiong and Zhang, 2010; Deshmukh and Bhosle, 2011). The increasing size and spatial resolution of remote-sensing images have increased the information that can be interpreted from very high-resolution (VHR) images. Many image registration methods have been proposed (Wong and Clausi, 2007; Hong and Zhang, 2008; Yu et al., 2008; Xiong and Zhang, 2009; Liu et al., 2012). However, most state-of-the-art methods have focused on small and medium-size images and ignored time performance; this lack of focus is a critical problem with regard to modern large-size images, especially in situations with limited processing time, such as risk response (Li, 2009; Zhang et al., 2009). High spatial resolution and large size also bring new challenges in remote-sensing image registration, as follows:

(1) Increased image spatial resolution (up to <1 m) has increased the typical scene of VHR remote-sensing images up to more than $10{,}000 \times 10{,}000$ pixels. Producing precise evenly distributed control points on large-size VHR images for registration is time consuming. Huo et al. (2012) reported that Lowe's standard scale-invariant feature transform (SIFT) algorithm without parameter tuning can extract approximately 400 MB of features from a typical $20{,}000 \times 20{,}000$-pixel remote-sensing image. Performing the SIFT algorithm on such large images also places a heavy burden on the memory of computing systems at hand. Matching such a large number of features also consumes considerable memory and time.
(2) Local distortion and relief displacement related to landscape height occur in remote-sensing images with high spatial resolution; thus, global transformation cannot be used to express the relationship among images for rectification as in traditional image registration (Xiong and Zhang, 2010). Even piecewise mapping has been used to rectify images, but detail and speed are ignored (Yu et al., 2008). Experimental images are often cropped from the original large-size image scene, only images with hundreds or thousands of pixels are used for experiment illustration, and the time performance of rectifying large-size images has not been well examined.

Despite these challenges, algorithms for VHR remote-sensing image processing can still be efficiently implemented with the help of advances in high-performance commutating technology, such as distributed networks, multi-core, and graphics processing units (GPUs) (Lee et al., 2011). Thus, this paper presents a method for large-size remote-sensing registration and uses GPU to accelerate the chain of registration processing. The rest of the paper is organized as follows. Section 2 reviews different approaches to remote-sensing image registration and high-performance computing in remote sensing image processing. The proposed method is described in detail in Section 3. Section 4 describes the experimental analysis and quantitative evaluation of large-size VHR images. Concluding remarks are presented in Section 5.

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2. Related work

2.1. Remote-sensing image registration

Modern image registration methods commonly include four steps: (1) feature extraction, (2) feature matching, (3) estimation of transformation functions, and (4) image transformation and resampling (Zitová and Flusser, 2003; Xiong and Zhang, 2010). Among these steps, feature extraction and feature matching are the most critical to accurately and efficiently registering images. Transforming and resampling excessively large-size images are also time consuming.

Several advanced methods for feature extraction have been developed, such as maximally stable extremal regions, SIFT, speed-up robust feature (SURF), and ORB (Matas et al., 2002; Lowe, 2004; Bay et al., 2008; Rublee et al., 2011). These methods are used to register remote sensing images because of their partially or fully invariant scale, affine changes, and illumination changes. However, such feature extraction and matching algorithms for computer vision are often originally designed for small images and thus cannot easily be adapted to large-size images, such as high-resolution satellite images.

Therefore, several of these feature extraction and matching methods have been modified to register high-resolution remote-sensing images. The feature detection algorithm is sensitive to setting parameters; thus, several methods have been proposed to control the spatial and scale distribution of detected features. For example, Zhu et al. (2007) proposed the use of information entropy to filter out features in poor texture areas and retain stable features for subsequent feature matching. Following this strategy, Cheng et al. (2008) proposed spatial filtering to ensure reliable feature matching. Sedaghat et al. (2011) also considered scale distribution and obtained uniform SIFT feature extraction results in spatial and scale space.

Compared with feature detection, feature matching has been the focus of more substantial efforts because of the scale, affine, and illumination changes in multi-model and multi-temporal remote-sensing images to be registered. For example, Li et al. (2009) proposed a scale-orientation constraint on SIFT feature matching. The mutual relationship and spatial consistency among features are used to constrain feature matching for reliable matching, such as for relaxation (Zhang et al., 2000; Zhang and Fraser, 2007; Wen et al., 2008). Aside from constraints, coarse-to-fine strategies and guided matching have been developed to enhance feature matching performance (Yu et al., 2008; Huo et al., 2012).

After control point detection, the transformation function estimated from these control points and image transformation is another crucial step in image registration. Several methods have been proposed for dealing with local deformations in images to be registered (Zagorchev and Goshtasby, 2006). The commonly used methods are often based on high-degree polynomial functions, such as thin plate spline and piecewise linear functions. Arévalo and González (2008) employed mesh optimization to improve piecewise registration results by considering the edge information from the corresponding scene. Wu and Goshtasby (2012) proposed the dynamic insertion of control points to generate a self-adaptive triangulated irregular network (TIN) to register images piecewise for a complex scene.

2.2. GPU computing in remote-sensing image processing

Given the increasing size of VHR images and the limited processing time in several situations, high-performance computing (HPC) infrastructure such as distributed networks, clusters, and specialized hardware devices, are widely employed to accelerate remote-sensing image processing. For example, Liu et al. (2010) adopted a clustered environment for ortho-rectification, and González et al. (2012) implemented an abundance estimation method for the spectral unmixing of hyperspectral data through an image space reconstruction algorithm based on a field-programmable gate array (FPGA). Both studies obtained excellent speedup.

Lee et al. (2011) reviewed advanced HPC on remote-sensing image processing, particularly hyperspectral image processing (Jeong et al., 2012; Bernabé et al., 2013). Specialized hardware devices, such as FPGA and GPU, facilitate real-time remote-sensing image processing. However, FPGA has to be integrated with many special skills before it can be used to accelerate computing; by contrast, GPU is flexible and programmable because of compute unified device architecture (CUDA), a parallel computing architecture developed by NVIDIA for GPUs (NVIDIA CUDA, 2013). Thomas et al. (2008; 2009) used GPU to achieve on-board ortho-rectification. Reguera-Salgado et al. (2012) implemented a GPU-accelerated method for line scanner image rectification. Both methods can process images in real time. Aside from the acceleration of image rectification by GPU, several studies have proposed the use of GPU to accelerate the process chain of image registration (Yoo et al., 2008a; 2008b). Biswal et al. (2013) found that approximately 85% of execution time in image registration is dominated by image transformation and resampling. Thus, the researchers implemented GPU-accelerated affine pixel transformation for real-time image registration. However, these methods used a simple global affine transform to rectify images.

GPU has also been used to accelerate commonly used feature detection methods, such as the SIFT and SURF algorithms (CUDA SURF, 2013; SiftGPU, 2013). These methods can be used to accelerate remote-sensing image registration with appropriate modification. Zanin et al. (2012) used SIFT and SURF implemented on a GPU to register aerial remote-sensing images and obtained desired results for unmanned aerial vehicle images. The researchers also reported that GPU-based feature detection accelerates registration processing, although they did not report any results on the registration of large-size images with significant deformation.

3. Methodology

3.1. Overview of the approach

The proposed method used two images: a reference image and a sensed image. The flow chart of the proposed method is shown in Fig. 1. The method includes three primary stages:

(1) Coarse registration (CR stage): In this stage, the original image is resized to accelerate SIFT extraction and matching. The RANdom SAmple Consensus (RANSAC) algorithm combined with estimation of homography transformation parameters is used to complete initial coarse registration.
(2) Fine registration (FR stage): Initial global transformation parameters are used to guide ORB feature extraction and matching in the reference and sensed images. The matches are then pruned iteratively by the RANSAC algorithm. The pruned matches are used as control points for registration.
(3) Image rectification (IR stage): After the control points are obtained, Delaunay's TINs are constructed, and the sensed image is rectified via a piecewise mapping function derived from the constructed TINs.

3.2. Coarse registration

3.2.1. SIFT extraction and matching

The SIFT algorithm is an excellent solution for identifying corresponding points on images with perspective and scale changes (Tuytelaars and Mikolajczyk, 2008; Wu et al., 2011). Therefore, the SIFT algorithm is used to determine the corresponding points for coarse registration. The standard SIFT algorithm and