ISPRS Journal of Photogrammetry and Remote Sensing 132 (2017) 1–19

Contents lists available at ScienceDirect

ISPRS Journal of Photogrammetry and Remote Sensing

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

An auto-adapting global-to-local color balancing method for optical imagery mosaic

Lei Yu [a], Yongjun Zhang [a], Mingwei Sun [a,*], Xiuguang Zhou [b], Chi Liu [a]

[a] School of Remote Sensing and Information Engineering, Wuhan University, Wuhan, Hubei, PR China
[b] Environmental Systems Research Institute, Inc. (ESRI), 380 New York Street, Redlands, CA 92374, USA

ARTICLE INFO

Article history:
Received 6 February 2017
Received in revised form 12 June 2017
Accepted 8 August 2017

Keywords:
Color balancing
Imagery mosaic
Global-to-local
Multi-type datasets

ABSTRACT

This paper presents a novel auto-adapting global-to-local color balancing method which aims to eliminate the effects of color differences between adjacent optical images to achieve seamless image mosaicking. The proposed method combines global and local optimization strategies to eliminate color differences between different target images adaptively without assigning the reference image. The global optimization strategy takes the constraint that the color information of the image before and after the color balancing process should be minimal, by which the assigning of reference images can be avoided. The strategy takes all target images as a whole and solves the normalization regression models simultaneously, which transfers the color difference elimination problem into the least square optimization one and eliminates the total color differences effectively. The local optimization strategy is a supplement for the global one, which focuses on the local information to eliminate the color differences in the overlap areas of the target images with the Gamma transform algorithm. It is worth noting that the proposed method can select a suitable processing flow from both the global and local optimization aspects based on the characteristics of the target images. When the total overlap rate of the target images is small, both the global and local strategies are employed; and when the total overlap rate of the target images is large, only the local optimization strategy is employed, by which a seamless color balancing result can be generated. The experimental results in this paper demonstrate that the proposed method performs well in color balancing for multi-type optical datasets.

1. Introduction

Mosaic images covering large areas have become increasingly important in the application of remote sensing (Chen et al., 2014; Cresson and Saint-Geours, 2015; Olthof et al., 2005). Due to factors such as the solar incident angle, atmosphere, and illumination condition, color differences exist between adjacent images, which makes image mosaicking a difficult process (Chen et al., 2005; Liu et al., 2014; Paolini et al., 2006) and hinders seamless mosaic data production.

The process of eliminating the color differences between different images is known as color balancing. A great number of color balancing researches have been conducted, which can be categorized as follows: direct methods, path propagation methods, and global optimization methods. Most of them designate a reference image and adjust the color information of the target image to that of the reference image (Carvalho et al., 2013; Zhang et al., 2014). The Wallis transform color balancing method (Jun, 2006; Sun and Zhang, 2008) and the Histogram matching method (Helmer and Ruefenacht, 2005; Lo and Yang, 2000; Tsai and Huang, 2005) are the representatives of the direct methods, which adjust the color information of every target image to that of the reference image directly. The direct methods are more suitable for the multi-temporal images covering the same area with small color differences (Lo and Yang, 2000); in other cases, color cast may exist due to the neglect of the real content of the target images. The propagation methods utilize the adjacent relationships between images to determine the color information transfer paths, through which the color differences between images can be eliminated in sequence. Li et al. (2015) proposed a local moment matching (LMM) algorithm to correct the tonal differences between different images. The LMM algorithm adopts the region-based adjustment strategy to avoid the overall luminance difference. Pan et al. (2010) proposed a network-based color equalization approach, which utilizes the adjacent relationships between the target images to determine the color

* Corresponding author.
E-mail address: Mingweis@whu.edu.cn (M. Sun).

http://dx.doi.org/10.1016/j.isprsjprs.2017.08.002
0924-2716/

information transfer paths, and the color difference between target images are eliminated one by one according to the transfer paths. However, the color error propagation and the two-body problems (Chen et al., 2014; Cresson and Saint-Geours, 2015) cannot be avoided in the propagation methods. The global optimization methods also build the color balancing models between the adjacent target images based on the color information in the overlap area. However, compared with the propagation methods, the global optimization methods are able to solve the color balancing models of all images simultaneously (Cresson and Saint-Geours, 2015), which convert the color balancing problem to a global optimization one. Sun et al. (2011) proposed a global optimization method based on the least square adjustment theory, which employed the adjacent relationship between images to build a linear color balancing model. The parameters of bias and scale are adopted in the linear color balancing model, which fit the color transformation relationship between adjacent images effectively. Due to the limitation of the number of model equations, the strategy of distribution solution is employed to calculate the bias and scale parameters. However, the hypothesis and the distribution solution used in Sun's method can lead to instability in the parametric model. Cresson and Saint-Geours (2015) converted the RGB values of the original images to a decorrelated color space named $l\alpha\beta$, then searched for the optimal parameters of color balancing models to minimize the cost function of the color differences between the target images. The method transferred the color balancing process into a quadratic programming issue to solve the color difference problem in a global way. The method is suitable for processing RGB satellite images only, and its procedures are relatively complex. Zhou (2015) proposed a multi-adaptive color balancing method which built a target color surface model as the reference color information to generate the color-balanced images. However, the method contains five color surface models which requires human interaction to select the suitable model for specific cases.

As is mentioned above, the selection of reference image is an important step for most of the existing color balancing approaches (Ibrahim et al., 2015), such as most of the direct methods (the Wallis transform color balancing method and the histogram matching method), the propagation methods (the network-based color equalization approach), and some of the global optimization methods (the least square optimization approach). However, the standard for determining the reference image is not unified (Yu et al., 2016). Brown and Lowe (2007) and Xiong and Pulli (2010) chose the reference image arbitrarily from the original target images or by the interaction of the user. It is obvious that the ways above are not the best choice for color balancing process. (Canty and Nielsen (2008) and Cihlar et al. (2003) selected the clearest image from the target images to be the reference image. However, the definition of "clearest" was not specified in their studies. Pan et al. (2010) and Chen et al. (2014) considered the image in the middle with the minimum distance to the other target images as the reference image, which did not take image quality into consideration. Recent years, some researchers proposed some color balancing methods without assigning the reference images. Cresson and Saint-Geours (2015) adopted the constraint that the sum of the mean values as well as the standard deviations of the target images is equal to that of the result images without assigning the reference image. However, their assumption may not work when the color information of the target images is distributed in a disorderly fashion, which may lead to color cast in the color balancing results. Zhou (2015) built a color surface model using the color information of the original target images to provide the reference information without assigning reference images. However, the color surface model may not well reflect the real color distribution of the target images, which leads to color distortions of the color balancing results.

There are many types of optical remote sensing images which, based on their acquisition platforms, can be classified as (1) satellite images, (2) aerial images, or (3) close-range images. Different types of images have different features. For example, satellite images provide wide coverage of ground objects and the overlap rate of the adjacent images is usually small, while aerial images usually have a high spatial resolution and large overlap rate between adjacent images. Most of the currently available color balancing methods focus on one of the remote sensing image type as the research target. The network-based color equalization approach and the least square adjustment approach take aerial images as the research data, while the quadratic programming method focuses on satellite images. Therefore, there exists a lack of researches on the common color balancing strategy for all types of remote sensing images.

To address this shortcoming, a novel auto-adapting global-to-local color balancing method (AGLCB) is introduced in this paper. The proposed method combines both the global and local optimization strategies, making it suitable for multi-type optical remote sensing images without reference images. As will be demonstrated in this paper, the proposed method can improve the existing methods in the following ways. (1) It can balance the image colors automatically without assigning reference images compared to the direct color balancing methods (Jun, 2006; Sun and Zhang, 2008; Helmer and Ruefenacht, 2005; Lo and Yang, 2000; Tsai and Huang, 2005). The method is able to avoid the color cast problem introduced by the assignment of a single reference image when the target images contain more than one category. (2) As far as the path propagation color balancing methods (Chen et al., 2014; Pan et al., 2010), the proposed method considers all the target images globally to calculate the color balancing parameters without the assignment of transfer paths, which are the sources of color error propagation and the two-body problem. (3) Finally, the proposed method, compared to the existing global optimization methods (Cresson and Saint-Geours, 2015; Sun et al., 2011; Zhou, 2015), converts the color balancing problem to a least square optimization one. Then a simple and robust local optimization strategy is employed to compensate for the color differences that still exist in local areas after processing by traditional global optimization methods.

2. Methodology

2.1. Overview

We consider that the target images needed to be color balanced are geometrically corrected, indicating that relative position relations exist among the target images. Therefore, the adjacent relationships and the overlap rates between the target images can be extracted easily according to the relative position information.

As is mentioned above, both global and local optimization strategies are combined in the proposed method. The global optimization strategy considers all the target images as a whole and solves the normalized regression models simultaneously, which can eliminate the total color differences effectively. However, due to the neglect of the local information of the target images, residual color differences may still exist in the overlap areas of the global optimization results. The local optimization strategy supplements the global strategy and focuses on the local information to eliminate the color differences in the overlap areas of the target images. The global-to-local color balancing method can not only effectively eliminate color differences between target images for multi-type optical remote sensing images, but also effective in optimizing color balancing workflow for different image types. As is mentioned above, the overlap rates between the target images can be extracted