Automatically eliminating seam lines with Poisson editing in complex relative radiometric normalization mosaicking scenarios

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ABSTRACT
Relative radiometric normalization (RRN) mosaicking among multiple remote sensing images is crucial for the downstream tasks, including map-making, image recognition, semantic segmentation, and change detection. However, there are often seam lines on the mosaic boundary and radiometric contrast left, especially in complex scenarios, making the appearance of mosaic images unsightly and reducing the accuracy of the latter classification/recognition algorithms. This paper renders a novel automatic approach to eliminate seam lines in complex RRN mosaicking scenarios. It utilizes the histogram matching on the overlap area to alleviate radiometric contrast, Poisson editing to remove the seam lines, and merging procedure to determine the normalization transfer order. Our method can handle the mosaicking seam lines with arbitrary shapes and images with extreme topological relationships (with a small intersection area). These conditions make the main feathering or blending methods, e.g., linear weighted blending and Laplacian pyramid blending, unavailable. In the experiment, our approach visually surpasses the automatic methods without Poisson editing and the manual blurring and feathering method using GIMP software.

KEYWORDS
Seam lines elimination; Poisson editing; Relative radiometric normalization; Image mosaicking; Histogram matching.

1. Introduction
A monthly/quarterly/annually updated sizeable remote sensing image containing the entire region of interest is crucial for downstream change detection tasks, geographic information system, and many other remote sensing applications, e.g., disaster monitoring, environmental monitoring, resource monitoring and geographical mapping. However, limited by the imaging width, mechanism and cloud coverage, a single remote sensing image often cannot cover the entire region of interest. However, suppose several remote sensing images obtained from different satellites, sensors or imaging times are directly mosaicked. In that case, a significant flower-cloth effect will appear (i.e., the mosaic image is not visually continuous.). This phenomenon is since different remote sensing images may be affected by imaging time, illumination effects, atmospheric attenuation, and other factors (Teillet (1986), Kim and Elman (1990)), resulting in radiometric distortion on the same object. Therefore, eliminating these
Researchers have proposed many methods to alleviate these distortions, but these distortions are not solved effectively because of the seam lines. Relative radiometric normalization (RRN) aims to reduce the global numerical colour/radiometric differences among multiple remote sensing images by modifying the original image’s colour/radiometric properties to match the reference image. Wallis filtering (Zhang, Zhang, and Zhang (1999), Shuo et al. (2019)) is one kind of methods, forcing different regions to have the same mean and variance. Some methods bases on histogram matching (Chavez and MacKinnon (1994), Horn and Woodham (1979), Weinreb et al. (1989)) and some further bases on matching on the overlap area (Helmer and Rufenacht (2005)). There are also other approaches including pseudo-invariant feature (Schott, Salvaggio, and Volchok (1988)), least square regression (Zhang et al. (2008)), establishing reference database (Zhang et al. (2017)) and etc. However, the methods mentioned above still need post-processing on seam lines to achieve a smooth transition. Besides, in the complex scenarios when there are lots of remote sensing images with different intersecting modes or extreme topological relationships, it becomes hard to use automatic feathering and blending methods to remove seam line. Therefore, people cost a lot of staffing and time to use Photoshop and other image editing software to manually edit remote sensing images.
Currently, seam lines eliminating methods, including mosaic line optimization, feathering and blending, utilizes overlapped area or vertical/horizontal seam lines shape, failing when the overlapped area is small. For instance, Santellani, Maset, and Fusiello (2018) utilizes Voronoi decomposition and colour contrast cost minimum distance mosaic line optimization to minimize the colour contrast on both sides of the mosaic line. Instead of eliminating the specified seam lines, this kind of methods generates a better mosaic line. However, this kind of methods usually cannot be perfectly seamless and may become ineffective when the overlapped area is small or the overlapped area has inner ring. Lu, Li, and Fu (2014) assumes the rectangular shape of the overlapped area and utilizes the 2-D linear weighted blending on the low frequency overlapped parts, and merges the images based on the mosaic line optimized by the high frequency overlapped parts. However, when the overlapped shape is not rectangular, or the overlapped area is small, this method becomes intractable or unhelpful.

Laplacian pyramid (Burt and Adelson (1987)) blending utilizes the mask on the overlapped area to construct different levels of blending Gaussian and Laplacian pyramids to reconstruct the blending image to eliminate seam lines. This kind of methods may hopefully overcome arbitrary seam lines on the rectangular overlapped area. However, when the overlapped area is small or complicated, the directly smoothing and down-sampling procedures of Laplacian pyramid blending become intractable. Moreover, Laplacian pyramid blending has to change the colour/radiometric of all the images on both sides of seam lines, and this can be a kind of distortion.

This paper presents a novel automatic approach for RRN mosaicking that uses the histogram matching on the overlap area to achieve relative radiometric normalization, Poisson editing to remove the seam line and sequence merging to determine the normalization transfer order. Compared with the traditional seam lines elimination methods, advantages of our method are as follows:

1. fully automatic;
2. widely applicable (it can overcome arbitrary seam lines shapes, complex overlapped shapes and small overlapped area.);
3. truly seamless with low distortion (instead of generating a new mosaic line, it achieves seamless transition by eliminating the colour contrast on one side of seam lines, reducing the distortion.).

2. Methodology

Suppose that we have a reference image and a set of other images. We can regard the reference image as the starting image of image mosaicking. The proposed method iteratively selects an original image intersected with the reference image and sequentially implements histogram matching, Poisson editing, and merging procedures to generate a new reference image. Repeating the procedures, we will finally obtain the complete mosaicking reference image.

In the following sections, we will first introduce the histogram matching method based on overlap area, and then introduce the Poisson editing on the complex boundary, and finally introduce the merging procedure.
2.1. Histogram matching based on overlap area

First, suppose the range of a remote sensing image is \([j_{\text{min}}, j_{\text{max}}]\), we can map it to \([i_{\text{min}}, i_{\text{max}}]\) where \(i_{\text{min}}, i_{\text{max}}\) are integers. The density histogram of an image is

\[
P(i) = \frac{N_i}{N},
\]

where \(N_i\) is the number of pixels that their grey scales equal \(i\) and \(N\) is the total number of pixels. The cumulative probability of the image is

\[
CP(i) = P(t \leq i) = \frac{\sum_{t=1}^{i} N_t}{N}.
\]

Suppose the overlapped area points set is \(S_{\text{overlapped}}\), and \(N_{t_{\text{overlapped}}}^{\text{O}}\) denotes the number of pixels in overlapped original image that grey scales equal \(t\) and \(N_{t_{\text{overlapped}}}^{\text{R}}\) denotes the number of pixels in overlapped reference image that grey scales equal \(t\), it yields the cumulative probability of the overlap of the original image and the reference image are \(CP_{\text{overlapped}}^{\text{O}}\) and \(CP_{\text{overlapped}}^{\text{R}}\) respectively:

\[
CP_{\text{overlapped}}^{\text{O}}(i) = \frac{\sum_{t=1}^{i} N_{t_{\text{overlapped}}}^{\text{O}}}{|S_{\text{overlapped}}|},
\]

\[
CP_{\text{overlapped}}^{\text{R}}(i) = \frac{\sum_{t=1}^{i} N_{t_{\text{overlapped}}}^{\text{R}}}{|S_{\text{overlapped}}|}.
\]

For pixel value \(i_{\text{O}}\) with cumulative probability \(CP_{\text{overlapped}}^{\text{O}}(i_{\text{O}})\), we can find the corresponding \(i_{\text{R}}\), which share the similar probability that

\[
i_{\text{R}} = \arg \min_i |CP_{\text{overlapped}}^{\text{R}}(i) - CP_{\text{overlapped}}^{\text{O}}(i_{\text{O}})|.
\]

It yields the mapping \(T_{\text{overlap}} : i_{\text{O}} \rightarrow i_{\text{R}}\). We apply the \(T_{\text{overlap}}\) to the original image then we achieve the histogram matching.

Since objects in the overlap area of the images are supposed consistent, when using the mapping \(T_{\text{overlap}}\) obtained from the histogram matching on the overlap area of the original image and the reference image, the radiometric value of the processed origin image incline to be consistent to the reference image’s radiometric value. Notice that if the reference image and original image only intersect on a small area and the overlapped area’s colour/radiometric diversity is insufficient, we skip this procedure and move to the Poisson editing procedure.

However, although the radiometric value can be consistent, there might be noticeable seam lines, especially when the intersection of the original image and reference image is complex or a slight difference occurs in the overlap area. Some feathering and blending methods are only suitable for simple intersection modes such as large rectangle intersection. However, they lose efficacy when the intersection is complex, or the intersection area is small, or the seam lines shapes are complicated, or the radiometric value contrast is too large. An efficient seam lines elimination is needed.
2.2. **Poisson editing on complex boundary**

Poisson editing introduces a guidance vector field from the source image to transplant the source image’s gradient vector field into a target region to achieve seamless filling (Pérez, Gangnet, and Blake (2003)). The central guiding ideology of Poisson editing assumes that seamless image function to be solved in $\Omega \in R^2$ space is $f$, the source image’s gradient vector field is $v$ and the boundary of the seamless image defined on $\partial \Omega$ is $f^*$ where $\partial \Omega$ is the boundary points of $\Omega$. The task is to find the optimal $f_{\text{optimal}}$ such that

$$f_{\text{optimal}} = \arg \min f \int \int_{\Omega} \| \nabla f - v \|^2 \text{ with } f|_{\partial \Omega} = f^*|_{\partial \Omega},$$

where $\| \cdot \|$ is the $L_2$ norm and $\nabla$ is the gradient operator. The minimizing problem is equivalent to solve:

$$f_{\text{optimal}} = \arg \min f \triangle f = \text{div} v \text{ over } \Omega \text{ with } f|_{\partial \Omega} = f^*|_{\partial \Omega},$$

where $\triangle$ is the laplace operator and $\text{div}$ is divergence operator.

The above equations are generalized to the discrete case (linear equations) to make the Poisson editing algorithm trackable, and we can further solve it by iteration methods. The detailed can refer to Pérez, Gangnet, and Blake (2003).

The important thing left is to determine the source point set $\Omega$ and the boundary function $f^*$ on $\partial \Omega$. The following shows how to obtain the $\Omega$ and $f^*$ on $\partial \Omega$.

First, we have the processed original image $I_O$ with point sets $S_O = \{p|p \in \text{origin image}\}$ and the reference image $I_R$ with point set $S_R = \{p|p \in \text{reference image}\}$. The example is illustrated in the following figure 3.

![Figure 3](image)

(a) reference point set $S_R$  (b) original point set $S_O$  (c) whole point set $S_O \cup S_R$

**Figure 3.** The illustration of the reference and original point set. The dark blue points are the intersection points.

Second, the target image $I_T$ is with the region $S_T = S_O - S_R^O$ where $-$ is the set difference and $S_R^O$ is the interior point of $S_R$. By the interior point of $S_R$, we mean that

$$S_R^O = \{q|q \in S_R, \text{ Neighbor}(q) \in S_R \text{ and } |\text{Neighbor}(q)| = 4\}$$

(8)
where \(\text{Neighbor}(q)\) is the set of \(q\)'s 4-connected neighbors. Besides,

\[
I_T(p) = \begin{cases}
  I_O(p) & p \in (S_O - S_R^O) - \partial S_R \\
  I_R(p) & p \in (S_O - S_R^O) \cap \partial S_R
\end{cases}
\]  

(9)

where \(\partial S_R = S_R - S_R^O\).

\[\text{Figure 4.}\ \text{The illustration of the reference interior, target and source point set. The dark blue points are the intersection points. The white points which don’t belong to the point set demonstrate original set’s boundary.}\]

The source image \(I_S\) is with the region \(S_S = S_T^O\) and \(I_S = I_O|_{S_S}\), that is \(I_S(p) = I_O(p)\ \forall p \in S_S\). It is obvious that the source image is contained in the target image, and the target image is modified slightly on the boundary point of the \(S_O - S_R^O\). The point value of \(I_R\) on \((S_O - S_R^O) \cap \partial S_R\) replaces of \(I_O\) on \((S_O - S_R^O) \cap \partial S_R\). Notice that replacement introduce the seam line between the boundary and the interior points. The example of the aforementioned point set is illustrated in the figure 4.

Finally, let \(\Omega = S_T\) and \(f^*|_{\partial \Omega} = I_T|_{\partial S_T}\), we can implement the Poisson editing to transplant source image to the target image and obtained the seamless image where the color contrast of the boundary and interior points are eliminated due to the guided interpolation.

Notice that the size of source image \(I_S\) might be pretty large, and it will cost many resources to solve the Poisson equation. Empirically, only the pixel value of the region in \(S_S\) that near \((S_O - S_R^O) \cap \partial S_R\) will be changed drastically after the Poisson editing. Therefore, we consider reducing the size of \(I_S\) in the actual implementation. Let

\[B_d(p) = \{q ||q_1 - p_1| + |q_2 - p_2| \leq d\},\]

(10)

and

\[B_d(S) = \bigcup_{p \in S} B_d(p)\]

(11)

We build a new source image \(I_{S_{new}}^S\) with \(S_{S_{new}}^S = S_S \cap B_d(S_T \cap \partial S_R)\) and \(S_{T_{new}}^S = S_T \cap B_{d+1}(S_T \cap \partial S_R)\). Let \(\Omega = S_{T_{new}}^S\) and \(f^*|_{\partial \Omega} = I_T|_{\partial S_{T_{new}}}\) implement the Poisson editing of the new source image to the target image. The choice of \(d\) depends on the size of \(I_O\) and depends on whether we implement the histogram matching procedure. If we skip the histogram matching procedure, \(d\) should be set to the maximum value to also eliminate global color contrast. The \(S_{S_{new}}^S\) is illustrated in the figure 5.
2.3. Merging

In order to let this procedure continue, we merge the seamless target image and the reference image. Notice that since the seam lines are removed, the merged image tends to be seamless and can be the new reference image shown in the figure 6 to participate in the latter repeated processing.

3. Experiments

3.1. Material and environment

We implement the algorithm and apply 34 resampled remote sensing multispectral images of GF-1 and GF-2 satellites in image mosaicking task.

These images partially cover the range of Qingdao, Shandong Province of China. These images were acquired in May 2019.

We performed the preprocessing steps of RPC orthorectication, radiometric calibration, atmospheric correction and Gram-Schmidt PanSharpening (Laben and Brower (2000)) on these images, and finally resampled the spatial resolution to 16m. The first three spectral are displayed.

We implement the algorithm on the computer with Inter(R) Xeon(R) W-2123 3.60GHz CPU and 32G RAM.
3.2. **Image mosaicking**

We use three automatic methods and one manual method with the help of GIMP image editing software (The GIMP Development Team (2019)). We use python to accomplish the automatic algorithm. Precisely, we first calculate the intersection of the square envelope of the reference image and the square envelope of the original image to speed up the calculation of the overlapped area and the determination of the blue boundary points \( S_T \cap \partial S_R \). The parameter \( d \) defined in equation 10 is set to 150 in this experiment. Then we use the sparse matrix of scipy library (Virtanen et al. (2020)) to construct the Poisson matrix and coefficient and use the algebraic multi-grid method with pyamg (Olson and Schroder (2018)) library to solve the Poisson equations. We use gdal library to merge the images.

The time-consuming algebraic multi-grid solving step of Poisson editing on about 4000 – 750000 points costs about 1 – 21 second. The average processing time on single remote sensing image ranging from about \((2000 \times 1500)\) to \((2900 \times 2400)\) is about 1.5 minute.

Figure 7 demonstrates the direct mosaic result, histogram matching result, histogram matching with Poisson editing result and histogram matching with GIMP manual seam line elimination. From figure 7, we can tell from the figure that histogram matching eliminates the colour contrast.

We provide the detailed image of the red point and yellow point in the figure 1 and figure 2.

According to figure 1 and 2, histogram matching on overlap area cannot deal with the boundary seam lines in the complex situation, including the boundary lake and multiple intersection areas. The colour difference on the different parts of the intersection area can cause colour inconsistency after histogram matching. The first case happened in the area shown in the figure 2, and these two cases happened together in the area shown in the figure 1. The upper-right remote sensing image in the figure 1 has more intersection with the image above rather than the intersection of image on the left, while the colour is different on these two images. As a result, it causes the colour difference on the lake. The manual edition blurs and makes the feathering effect on the image and alleviate the seam lines. In contrast, the Poisson editing can eliminate the seam lines on the complex situation and spread the colour to the expansion region and make the transition smooth. Compare to the four methods, the histogram matching on overlap area with Poisson editing method has the best effect.
Figure 7. The comparison figure of the four methods.
4. Conclusion

This paper presents a novel automatic approach for eliminating seam lines in RRN mosaicking tasks. It utilizes the histogram matching on the overlap area to achieve colour/radiometric normalization, Poisson editing to remove the complicated seam lines in diverging intersecting modes and merging to achieve seamless mosaicking finally. It is fully automatic, overcoming arbitrary seam lines shapes, complex intersecting modes and small overlapped area. Our method visually surpasses the automatic methods without Poisson editing in the experiment and the manual blurring and feathering method using GIMP software.

Currently, our method is independent of the mosaic line optimization algorithm, and it can easily incorporate with the optimized mosaic line. Besides, our method also naturally applies to cloud inpainting task. In the future, we will investigate how to accelerate the Poisson editing procedure to let this algorithm be more efficient than the current version.

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Disclosure statement

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