Landsat-8 Image Restoration Based on Kernel Density Regression

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Abstract. A multi-temporal kernel density regression (KDR) method is proposed in this paper for reflectance restoration. Kernel density regression perform optimization to search the best regression coefficients. The proposed method is applied on the Landsat-8 dataset, and shows a better estimation of the true pixel value from the contaminated images.

Keywords: Reflectance restoration · Multi-temporal · Kernel density regression

1 Introduction

Clouds are the biggest occlusion in the optical remote sensing images. Since electromagnetic waves can be strongly attenuated and interfered when reflected in the cloud layer, the quality of the optical remote sensing image is greatly reduced due to the reflection of the cloud, and the accuracy of the optical application results is greatly reduced. Therefore, it is crucial to retrieve the landscape reflectance from cloud corrupted images.

Fmask algorithm [1] is a kind of object-based method, which uses the precise measurement of Near Infrared (NIR) Band and the Brightness Temperature

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(BT) for cloud and cloud shadow detection of Landsat-8 data. The algorithm needs a lot of information, e.g. the satellite sensor‘s view angle, the illuminating angle, brightness, spectral variability and temperature probability, etc. By this method, a relatively accurate cloud shape detection can be obtained. However, because of the difficulty of getting the prior information motioned above, the practicality of Fmask is greatly reduced when the images of the land is the only information we have.

The number of works focused on reflectance restoration in optical remote sensing images with time series is quite small. When there is no cloud in the sky, the reflection of the underlying landscape is usually small due to the continuity of the natural landscape. When the cloud appears, the pixel value will change greatly. Most multi-temporal methods detect clouds by analyzing pixel quality changes in time-series images.

Another algorithm adopted the method based on adaptive threshold is multi-temporal cloud detection (MTCD) [3]. The reflectance variations in both red and blue bands is recorded. The result is that although the algorithm shares an effective competence, the high requirement of a clear reference image with little or no cloud covered weaken its practicality. Besides, one of our conference paper [5] applies mean shift algorithm to extract the pixels' model through multi-temporal images and a cloud-free image is created. The cloud is then detected by thresholding the difference pixel value between the target image and reference image.

Creating a different reference image at each moment is a more efficient and reasonable approach from a more realistic perspective. In this article, we exploit KDR to restore pixel values in multi-temporal images which is contaminated by clouds. We determine the pattern of changes for each pixel based on the time series, while providing a recovered image for each moment. By KDR process, we can get the best regression coefficients and the clear restored images of underlying landscape for the whole time series. Through the kernel density estimation, the probability density of the residual value is calculated and we choose the coefficient corresponding to the maximum probability density as the regression coefficient. Then we can use the regression function to estimate the true pixel value.

2 Methodology

Suppose that:

$$y_i = f(x_i) + \varepsilon_i, i = 1, 2..., n \tag{1}$$

where $f(\cdot)$ is the regression function, y_i is the measurement which gives reflectance of one pixel at sampling instant x_i, n is the number of the samples. Because the cloud layer has a big impact on the detected pixel quality, the measurement y_i could deviate far away from the true reflectance of the pixel in some times.

Since in the natural world, the ground landscape usually changes continuously, so the pixels' reflectance always changes slowly in image series. Therefore, the function $f(\cdot)$ can be assumed to be of an 3-order local smoothness, i.e., the model can be approximated as:

$$y_i = \beta_0 + \beta_i x_i + \beta_2 x_i^2 + \beta_3 x_i^3 \tag{2}$$

Let $X_i = [y_i, x_i, x_i^2, x_i^3]^T$, $\beta = [-1, \beta_1, \beta_2, \beta_3]^T$, we have

$$\beta^T X_i + \beta_0 = 0, i = 1, 2..., n \tag{3}$$

Thus the problem of solving coefficients of the polynomial becomes the problem of searching the parameter β and β_0 which fit all of the data $\{X_i, i = 1, 2, ..., n\}$ best, and it equals pursuit a unit normal vector $\alpha = \beta/norm(\beta)$, norm$(\cdot)$ is a normalization function, and $\alpha_0 = \beta_0/norm(\beta)$. In the solving process, we firstly set a normalized vector α, and then perform orthogonal projection of each X_i on it, we will obtain n projected values. If the true vector α is selected for projection, the projected values will concentrate at $-\beta_0$. We introduce the metric of kernel density estimation to make quantitative analysis of concentration. We use the kernel function $K(\cdot)$ to find the probability density function of its distribution $p_\alpha(\cdot)$:

$$p_\alpha(u) = \frac{1}{Nh_\alpha} \sum_{i=1}^{n} K(\frac{u - \alpha X_i}{h_\alpha}) \tag{4}$$

where $p_\alpha(u)$ is the density estimate at point u, N is the total number of the points of the sample set, h_α is the bandwidth of kernel function with certain α.

Here we use the Epanechnikov function [6] as the kernel function $K(\cdot)$:

$$K(x) = \begin{cases} \frac{3}{4}(1 - x^2), & x^2 < 1 \\ 0, & else \end{cases} \tag{5}$$

The probability density function $p_\alpha(\cdot)$ can reflect if we find the true parameter α, $p_\alpha(\cdot)$ will have the maximum peak if the true vector α is found, and the mode is $-\alpha_0$.

Then the optimization of the parameter, i.e., $\hat{\alpha}$, can be calculated as:

$$\hat{\alpha} = arg \max_{\alpha} p_\alpha(u) \tag{6}$$

By solving this optimization problem, we can get the regression coefficients $\hat{\alpha}$ and the true value of the pixel value y_i can be estimated by the regression as:

$$\hat{y}_i = -\frac{\alpha_0}{\alpha_1} - \frac{\alpha_2}{\alpha_1} x_i - \frac{\alpha_3}{\alpha_1} x_i^2 - \frac{\alpha_4}{\alpha_1} x_i^3 \tag{7}$$

which corresponds to the clear pixel at time i.

The gray information algorithm is used in this paper to deal with the multi-temporal optical remote sensing images for reflectance restoration. The method is divided into two parts. The first step is preprocessing (i.e. calibration, region of interest selection) and the second is reflectance restoration. The data preprocessing is that co-registering all the images in Landsat-8 OLI dataset before the process of value restoration of pixels, which allows a cloud-contaminated image to be fully acquired in a fixed area in one year. In order to reduce the computational complexity of processing the whole images of the dataset, we use some sub-images that cropped out from the registered images for the purpose of results demonstration. After the preprocessing above, the restoration result of kernel density estimation algorithm is shown on the set of sub-images in Sect. 2.

Here we denote $D = \{S_1, S_2, ..., S_{25}\}$ with $S_i \in R^{M \times N}$ the sub-image dataset of a certain area at 25 time instants. The reflectance of that underlying landscape is assumed as changes slowly and gradually within a short time period. However, if the land is contaminated by cloud or other optical contaminant, the pixel's reflectance will have a sudden change.

Here we select the pixel at (m, n) as an example to illustrate the effect of the algorithm. The Landset-8 satellite scans the same place every 16 days and after 25 times of scanning, pixel located at (m, n) can obtain 25 reflectance measurements, which can be denoted by notation above as $D_{m,n} = \{S_1(m, n), S_2(m, n), ..., S_{25}(m, n)\}$. Equation (7) provided the robust regression estimate of $D_{m,n}$ and the cloud can be detected if the pixel value is far away from the model. In Fig. 1, it gives the regressed reflectance result of given $D_{m,n}$, and the robust regression result is denoted by the red line and the cloud corrupted measurements are denoted by the blue star line. It can be noted that the outliers with pixel values 66, 45 at time instants 13, 14 correspond to thick cloud and those with pixel values 36 at time instants 17 correspond to extremely thin cloud. Through kernel density estimation we can find the best fit coefficients. Kernel density function of the projection $\alpha^T X_i + \alpha_0$ of the pixel located at (m, n) have one largest main peak which close to zero. Figure 2 gives the result of kernel density function with respect to the pixel at (150,150). The maximum value of the probability density function is at the zero point of the coordinate axis, and the highest peak of the kernel density estimation is also at zero point, so it can be explained that the regression equation is very close to the original pixel value.

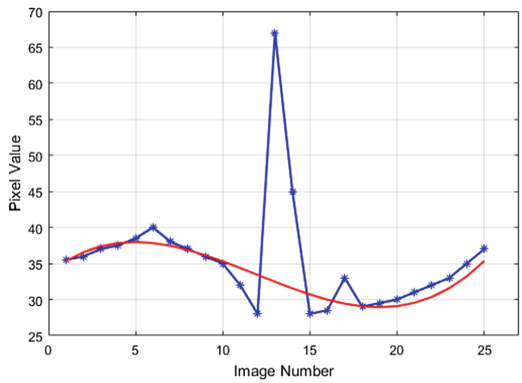

Fig. 1. Cloud corrupted pixel value against the time series and the kernel density estimation based regression. (Color figure online)

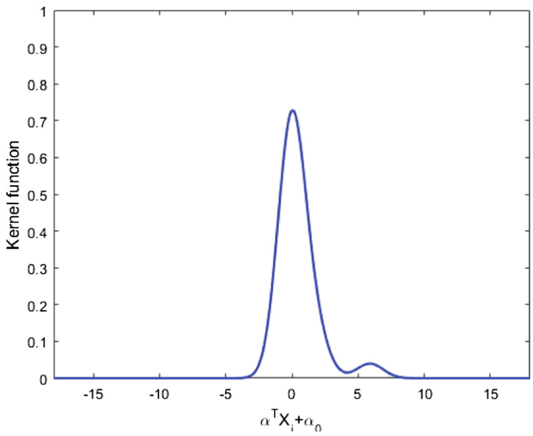

Fig. 2. The estimated probability density function after KDR.

3 Preliminary Results

For validating the effectiveness of the algorithm, our algorithm is tested with the time series data of Landsat-8 OLI images of 011/036 (path/row) acquired from 15 March, 2013 to 2 July, 2014, which can be downloaded at http://earthexplorer.us.gs.gov. The images centered at $34°55'10"N$ and $74°7'15"W$ were near Norfolk, Virginia, USA. A set of sub-image with configuration of 501 (columns) $\times$ 501 (rows) were extracted from each image in dataset. The illustration of the images we used in this time series can be found in Fig. 3, where the images are sorted line by line in order of time growth.

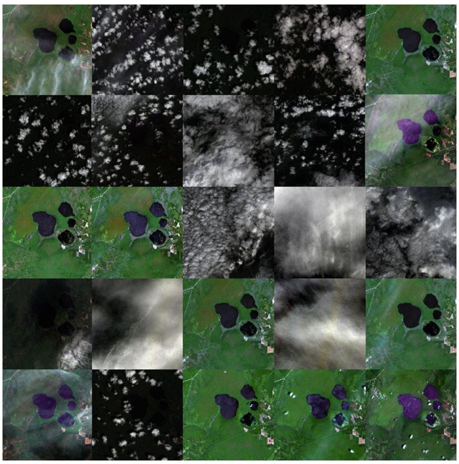

Fig. 3. Raw RGB images sorted by time. (Color figure online)

Figure 4 gives the image restoration results obtained by the proposed algorithm at 14^{th} time instant, and we choose the original image at 12^{th} time instant as ground truth, herein we assume the landscape changes little since the shot time of the two images is only one month apart. It is noted in Fig. 4 that the proposed kernel density estimation based reflectance restoration algorithm has a good performance.

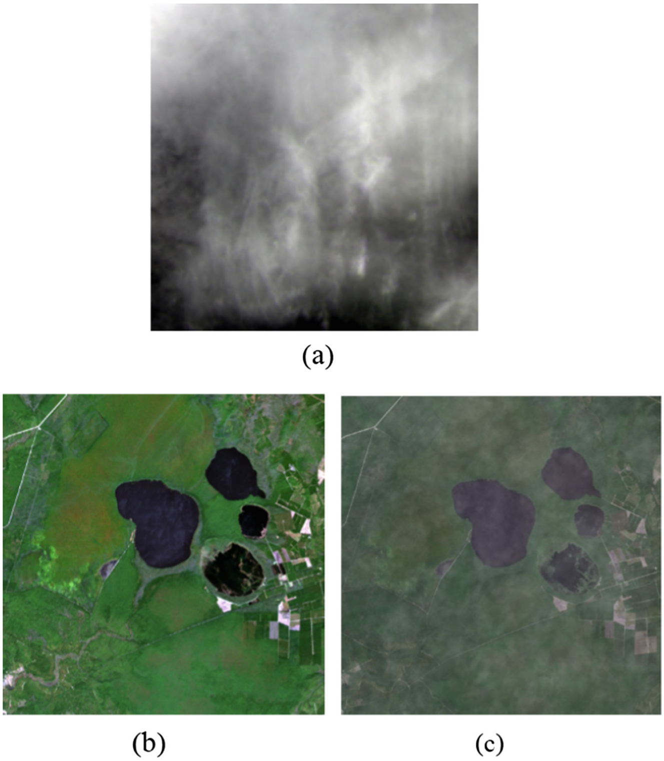

Fig. 4. Image restoration result at 14th time instant. (a) Original cloud contaminated image; (b) The original image in the 12th time instant; (c) The result of the proposed method.

4 Conclusion

A multi-temporal reflectance restoration method is proposed in this article by kernel density estimation regression model. With this method, we can obtain a cloud free image at any time instant. It can work automatically without reference image. For each time instant, a restored image is produced by fitting robustly of the pixels of the multi-temporal images corrupted by the cloud. Those restored images show the inherent gradual change of the landscape with time instants.

The limitation of the method is that the effect of extremely thin cloud components cannot be avoid and the degree of reduction of images in urban areas is relatively low because the difference between the reflectance and the pixel value corrupted by cloud is too small to discriminate.

References

1. Zhu, Z., Woodcock, C.E.: Object-based cloud and cloud shadow detection in Landsat imagery. Remote Sens. Environ. **118**, 83–94 (2012)
2. Li, M., Liew, S., Kwoh, L.: Automated production of cloud-free and cloud shadow–free image mosaics from cloudy satellite imagery. In: Proceedings of the ISPRS Congress, Istanbul, 12–13 July 2004 (2004)
3. Hagolle, O., Huc, M., Pascual, D.V., Dedieu, G.: A multi-temporal method for cloud detection, applied to FORMOSAT-2, VENuS, LANDSAT and SENTINEL-2 images. Remote Sens. Environ. **114**(8), 1747–1755 (2010)
4. Han, Y., Kim, B., Kim, Y., Lee, W.: Automatic cloud detection for high spatial resolution multi-temporal images. Remote Sens. Lett. **5**(7), 601–608 (2014)
5. Qian, J., Luo, Y., Wang, Y.: Cloud detection of optical remote sensing image time series using mean shift algorithm. In: IEEE International Geoscience and Remote Sensing Symposium (IGARSS), pp. 560–562 (2016)
6. Epanechnikov, V.A.: Non-parametric estimation of a multivariate probability density. Theory Probab. Appl. **14**, 153–158 (1969)