A Method to Destripe Imaging Spectroradiometer Data of SZ-3

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Abstract: Striping is a main factor for imaging spectroradiometer data, which is obtained by multi-sensor scanning on spacecraft. The reason causing stripes and the development of striping removal methods are simply described in this paper, particularly, the principle of Matching Empirical Distribution Functions is introduced in detail. By using this method, some experiments are done to destripe imaging spectrometer data of SZ-3. The result shows that the method of Matching Empirical Distribution Functions is available for destirping Imaging spectroradiometer data of SZ-3, and the quality of image is improved obviously. This will help to process the future similar instruments data.

Key words: Imaging, Spectroradiometer, Sensor, Destripe, Empirical Distribution Function

1. Introduction

As the development of remote sensing technology, not only high temporal and spatial resolution but also the large surface area are required. In order to realize this requirement, many instruments on satellite are designed to scan the earth by using multiple sensors, such as Moderate Resolution Imaging Spectroradiometer (MODIS) on EOS, the most visible channels of scanning radiometer on geostationary meteorological satellite, the imaging spectroradiometer on Chinese SZ-3 airship. When scientists use this kind of data, they meet a universal problem, the data quality is not so good. Imagery of data always shows periodic striping, different with single sensor noise, and as time on, this character becomes more serious. Mainly it is caused by differential sensitivities of sensors to incoming radiation. Therefore, striping is a primary character on image acquired from multisensor instruments.

The striping of imagery affects the quality of data, it also brings big trouble for calibration, and for this reason, and it affects quantitative calculation of earth physical parameters and the accuracy of products. To destripe imagery of data becomes more important and useful.

2. Method

Scientists have developed some methods on destriping imagery. Horn et al. [1] (1979) used histogram modification to destripe Landsat MSS images. Kautsky et al. [2] (1984) developed a method by smoothed histogram modification for image processing. In 1989, Weinreb et al.[3] destriped GEOS image by matching empirical distribution functions. In the same year, Crippen[4] used simple spatial filtering routine for the cosmetic removal of scan-line noise from Landsat TM P-tape imagery. Wegener (1990) [5] used improved histogram matching to destripe multiple sensor imagery. In 1998, Srinivassan et al.[6] destriped Landsat data by using power filtering. Gadallah et al.[7] (2000) developed a way with moment matching, Liu et al. [8] (2002) improved this way.

These methods can be concluded two types. One is filter, and another is sensor count matching. Filter can remove striping, but it also loses some useful information. In this view, when the data will be used to derive some physical parameters, the second type is better, for it almost keeps all information, and data can be transform each other.

In our approach, we destripe imaging spectroradiometer data of SZ-3 by matching empirical distribution function, which is developed by Weinreb et al. in 1989.

In theory, when several different sensors view the same scene, their outputs should be equal, and this should be no matter what the scene is. In fact, this is an ideal condition, the outputs always have some differences, mainly are caused by the physical and mechanical performances of sensors, synthetically called sensitivity. There is no two sensors ever view the same scene in the actual application. However, for a large ensemble of measurements, the distribution of the intensity of the earth radiation incident on each sensor will be similar. With this assumption, the distributions of the outputs of each sensor should be identical.

Therefore, when one sensor's distribution of the intensity is known, others are almost the same. The key point is to select a standard sensor among all sensors. Considered the performance of sensors, the standard one should be chosen on the basis of its relative stability, low noise, and maximal use of the dynamic range of the data system without clipping at either the low or high ends. According to the distribution, the outputs of other sensors can be adjusted with normalization tables.

To calculate the sensor's distribution of the intensity, a way called Empirical Distribution Function (EDF) is to do a cumulative intensity for every count. It can be expressed as

$$P_i(x) = \sum_{y=0}^{x} p_i(y) \quad (1)$$

where the subscript i refers to sensor number, $p_i(y)$ is the intensity for count x of sensor i, $P_i(x)$ is the cumulative intensity which the count is from 0 to x. This function is a non-decreasing function of x, and its maximum value is unity. Here, we choose the maximum value to be 1. It means when output x equals to X, then

$$P_i(X) = 1 \quad (2)$$

According to the assumption, each output value x in sensor i, the normalizes value x' should satisfy

$$P_s(x') = P_i(x) \quad (3)$$

where the subscripts refers to the standard sensor. In practice, not only is P_s non-decreasing, but it is also monotonically increasing as a function of x' in the domain of x' where there are data. Consequently, it can be inverted, and the solution for x' can be written as

$$x' = P_s^{-1}[(P_i(x)] \quad (4)$$

Equation(4) shows the relation between x and x', this is the basis to generate a normalization look-up table relating each x and x'. Figure 1 illustrates how it works in actual practice to generate the content in the table. The figure show us the idealized EDFs for standard sensor and sensor i. The EDF curves in the figure are continuous, however, they are discrete in practice because the counts (x) are integers. For this reason, it should be interpolated within the EDF of standard sensor to find the value of x' that x corresponds.

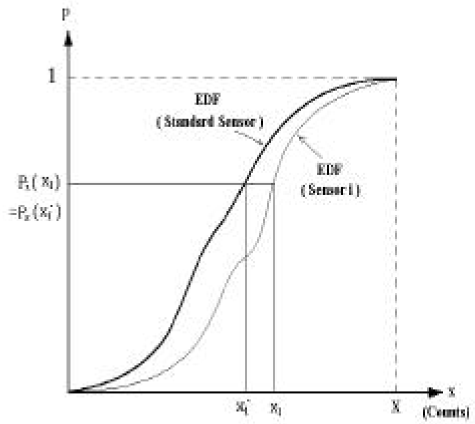

Fig 1. Illustration of procedure to generate normalization look-up table

3. Data Process and Analysis

Imaging spectroradiometer on SZ-3 has 34 channels, 30 channels locate in visible and near-infrared band, which arrange from 401nm to 1018nm. Both interval and the width between channels are about 20nm. The other 4 channels locate mid and far infrared, they are 2.15~2.25μm, 8.4~8.9μm,10.3~11.3μm and 11.5~12.5μm. The spatial resolution in nadir is about 500m, every channel scanner is made of 22 sensors, the dynamic range of the data are from 0 to 4095 (12 bit).

Figure 2 shows a part of image in channel 3 (440-460nm), periodic striping is very obvious, the width is 22 lines, and this number is the same as sensors.

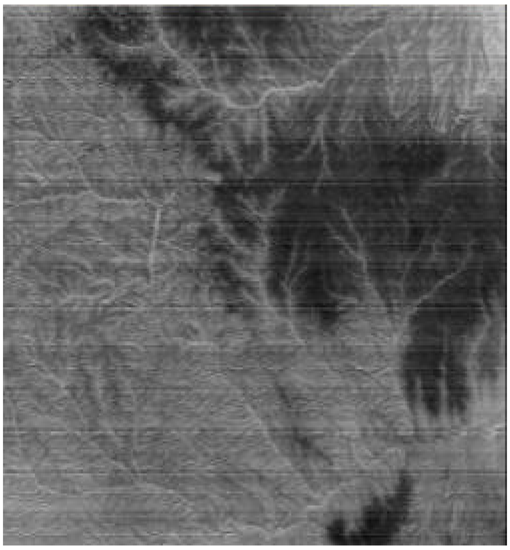

Fig 2. Raw image of channel 3 for imaging spectrometer data of SZ-3

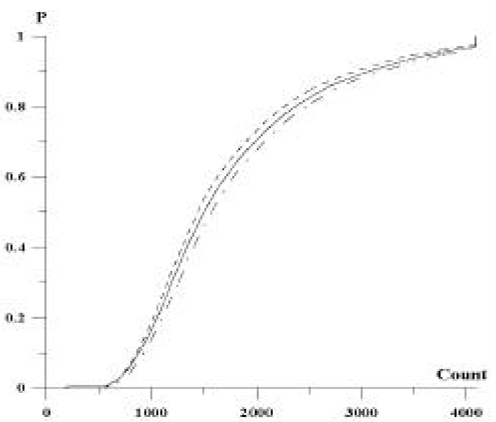

Fig 3. Fig.3 Empirical distribution functions at channel 15 for unnormalized parts of sensors data for SZ-3 76th orbit, (- - -) Sensor 1, (—) Sensor 3, (- · - ·) Sensor 22

After analyzing every sensor data, we find sensor 3 is best one, so this sensor is selected as standard sensor.

By using above method, we get EDFs for every sensor and look-up table, Figure 3 shows the EDFs for three sensors, others have the similar shapes.

After adjusted by look-up table, image looks much better than unnormalized image. Figure 4 is the normalized image.

4. Conclusion

After processing several hundreds orbit data for SZ-3, we find that normalization by EDF matching is an effective method for destriping imagery from imaging spectroradiometer on SZ-3. The Chinese new generation polar orbit meteorological satellite named FY-3 will be istalled similar imaging spectroradiometer,

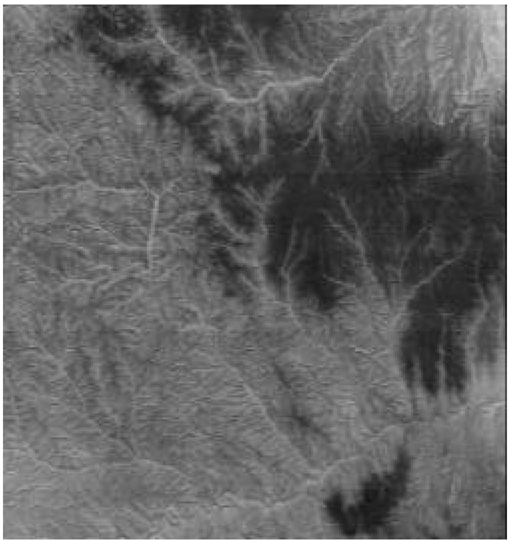

Fig 4. Normalized image, others are same as Fig. 2.

we hope this method will help us to process the data in future.

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