

AUTO-DETECTION OF HETEROGENEOUS AREAS IN RADIOMETRIC NORMALIZATION

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ABSTRACT:

Due to the difference in illumination condition, atmosphere condition, shooting angle and other inner and outer factors, there are differences in radiometry between different optical remote sensing images. The radiometric differences will affect the mosaic result and further affect some applications. To minimize such radiometric differences, radiometric normalization between images is a useful pre-processing step. However, there are often some heterogeneous areas in images. They are harmful to the radiometric normalization and even lead to the failure of the radiometric normalization. So it is necessary to detect these areas automatically. In order to achieve a more accurate result about the heterogeneous areas at the given scale, this paper based on the idea of SR (Super resolution) proposals an auto-detection method for heterogeneous areas using texture information. Then those heterogeneous areas are excluded during the generation of statistics for the radiometric normalization. Experiments indicate the approach proposed by this paper is feasible and the effect of radiometric normalization is also improved obviously.

1. INTRODUCTION

Change detection is useful in many applications such as land use changes, habitat fragmentation, rate of deforestation, coastal change, urban sprawl, and other cumulative changes through spatial and temporal analysis techniques such as GIS (Geographic Information System) and Remote Sensing along with digital image processing techniques. In order to do change detection in large area, it is needed to joint many small digital images into a big one, i.e. mosaic. But due to the difference in illumination condition, atmosphere condition, shooting angle and other inner and outer factors, there are differences in radiometry between different optical remote sensing images. The radiometric differences will affect the mosaic result and further affect the change detection analysis. To minimize such radiometric differences, radiometric normalization between images is a useful pre-processing step prior to change detection analysis for large area.

However, in large area the scene is very complex, and there are often some heterogeneous areas in images. The most typical heterogeneous areas are water areas. These areas are harmful to the radiometric normalization and even lead to the failure of the radiometric normalization. So it is necessary to detect these areas automatically and exclude them during the generation of statistics for the radiometric normalization between images.

Since the texture information of heterogeneous areas such as water areas in images is different from other areas, it is possible to detect such areas automatically. After splitting an image into many blocks without overlap, this paper use the statistic of each image block to detect the heterogeneous areas. Whereas, due to the scale issue, heterogeneous features in small scale are likely to become homogeneous features in large scale. So it is not the

fact that more small scale will bring more accurate detected result. We should improve the detection accuracy at a certain scale.

Super resolution (SR) image reconstruction is a new image processing branch, which restores one better image of higher resolution from a degraded image sequence of lower resolution (LR). If there are sub-pixel shift in LR images for same scene, SR reconstruction is possible. In order to achieve a more accurate result about the heterogeneous areas at the given scale, this paper based on the idea of SR proposals an auto-detection method for heterogeneous areas using texture information.

This paper divides the image twice using the given scale. The second division has a half scale shift compared to the first division. Then based on the two detection results from twice division, this paper achieves heterogeneous areas with higher "resolution". When getting heterogeneous areas, it is available to exclude them during the generation of statistics for the radiometric normalization. By this means, the effect of radiometric normalization can be improved obviously.

2. METHOD

2.1 Radiometric Normalization

Radiometric normalization is the processing to maintain the radiometric consistency between different images. It is also called the relative radiometric correction. In performing relative radiometric normalization, one usually makes the assumption that the relationship between the at-sensor radiances recorded at two different times from regions of constant reflectance can be approximated by linear functions. The critical aspect is the

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determination of suitable time-invariant features upon which to base the normalization. It is also what many researchers concentrate on and many methods have been presented from the initial manual to the full automatic selection time-invariant features (Canty et al., 2004; Canty et al., 2007; Du et al., 2002; Furby and Campbell, 2001; Hall et al., 1991; Moran et al., 1992; Nielsen, 2007; Schott et al., 1988; Schmidt et al., 2005; Schroeder, 2006; Yang et al., 2000).

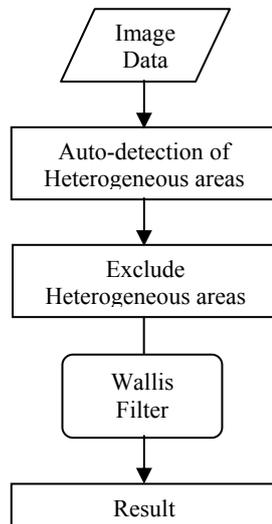


Figure 1. Processing flow of radiometric normalization using global methods based on the auto-detection of heterogeneous areas

But if the radiometric differences between images can not be represented by the overlap area or the geocoding information is not available, the above methods will not be suitable. Then we should use the global methods to do radiometric normalization. The Wallis filter is the typical global method for the radiometric normalization between different images. It adjusts the radiometric differences based upon values of global mean and standard deviation. But the heterogeneous areas in images are harmful to the radiometric normalization and even lead to the failure of the radiometric normalization. So it is necessary to detect these areas automatically and exclude them during the generation of statistics for the radiometric normalization between different images. The processing flow of radiometric normalization using global methods based on the auto-detection of heterogeneous areas is depicted as follows Figure 1.

2.2 Wallis Filter

Wallis filter is a special filter, and now it has been used widely in digital image processing. It can map the mean and standard deviation of local area image to the given values. In fact, it is a kind of local image transform and can make different areas of image with similar mean and deviation. It can enhance the areas with low contrast and depress the areas with high contrast. The Wallis filter can be denoted as:

$$f(x, y) = \left[g(x, y) - m_g \right] \frac{cs_f}{cs_g + (1-c)s_f} + bm_f + (1-b)m_g \quad (1)$$

In formula, $g(x, y)$ denotes the pixel value of original image; $f(x, y)$ denotes the pixel value of output image after Wallis transform; m_g denotes the local mean of original image; s_g denotes the local standard deviation of original image; m_f denotes the local target mean of output image; s_f denotes the local standard deviation of output image; $c \in [0,1]$ denotes the expand const of standard deviation; $b \in [0,1]$ denotes the luminance coefficient of image. When $b \rightarrow 1$, the mean of image is forced to m_f , and when $b \rightarrow 0$, the mean of image is forced to m_g . The filter also can be denoted as:

$$f(x, y) = g(x, y)r_1 + r_0 \quad (2)$$

In formula, $r_1 = \frac{cs_f}{cs_g + (1-c)s_f}$,

$r_0 = bm_f + (1-b-r_1)m_g$; r_1 and r_0 denote the multiplicative coefficient and additive coefficient (Zhang et al., 1999; Wang et al., 2000).

An image's mean reflects its tone and luminance, and standard deviation reflects its dynamic range of pixels' value and its contrast. At one hand, due to the relativity of the adjacent features, multi-images captured in ideal cases should be continuous in color space and have approximately consistent tone, luminance, contrast and similar dynamic range. So they should also have similar global mean and standard deviation. Therefore, it is a necessary condition for multi-images to have similar global mean and standard deviation. On the other hand, due to the features in the real scene are continuous in color space, though there are changes and differences between multi-images in color, the changes and differences within the scene generally are few and localized. So it is a sufficient condition for multi-images to do radiometric normalization using reference parameters.

2.3 Super Resolution

The basic premise for increasing the spatial resolution in SR techniques is the availability of multiple LR images captured from the same scene (see [4, chap. 4] for details). In SR, typically, the LR images represent different "looks" at the same scene. That is, LR images are subsampled (aliased) as well as shifted with subpixel precision. If the LR images are shifted by integer units, then each image contains the same information, and thus there is no new information that can be used to reconstruct an HR image. If the LR images have different subpixel shifts from each other and if aliasing is present, however, then each image cannot be obtained from the others. In this case, the new information contained in each LR image can be exploited to obtain an HR image. To obtain different looks at the same scene, some relative scene motions must exist from frame to frame via multiple scenes or video sequences. Multiple scenes can be obtained from one camera with several captures or from multiple cameras located in different positions. These scene motions can occur due to the controlled motions in imaging systems, e.g., images acquired from orbiting satellites. The same is true of uncontrolled motions, e.g., movement of local objects or vibrating imaging systems. If these scene motions are known or can be estimated within subpixel accuracy and if we combine these LR images, SR image

reconstruction is possible as illustrated in Figure 2 (Park et al., 2003).

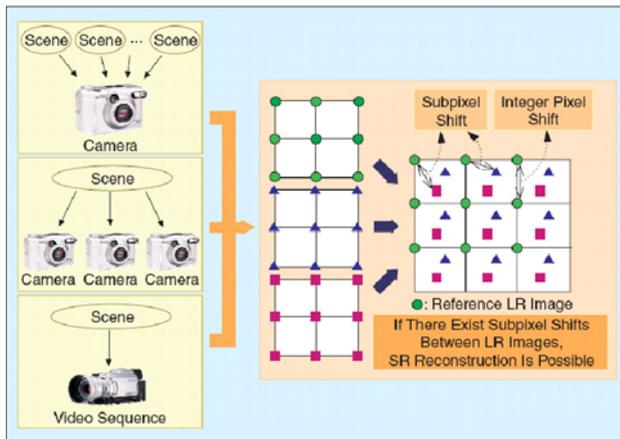


Figure 2. Basic premise for super resolution

2.4 Auto-detection of Heterogeneous Areas Based on SR idea

The most typical heterogeneous areas are water areas. They will affect the effect of radiometric normalization when using the global methods. So it is necessary to do special processing to these areas and exclude them when radiometric normalization between multi-images for better effect. Since the texture information of large water areas in images is weak compared with other areas, water areas can be auto detected using statistic about texture. The deviation of image reflects the intensity of texture, so it is available to using deviation as the statistic to detect the water areas in images.

The auto-detection steps are as follows:

- 1) Decide a scale for the detection of heterogeneous areas.
- 2) First division. Divide an image into blocks without overlap areas and there are not offset in both x and y direction;
- 3) Statistic the local deviation of each image block;
- 4) Set a threshold for deviation, and if the local deviation is smaller than the threshold, the image block is looked as a heterogeneous area. Save the state of each block and it is the first "LR" data;
- 5) Then merge adjacent heterogeneous image blocks to form initial heterogeneous areas;
- 6) Second division. The second division has a half scale shift compared to the first division. There are an offset of a half scale in both x and y direction;
- 7) Do the step 3)-4) and get the second "LR" data;
- 8) Combine the two "LR" data with "sub-pixel" shift to achieve heterogeneous areas with higher "resolution".

3. EXPERIMENTAL RESULT

Figure 3 shows two images among the experimental image data set for the radiometric normalization. It can be noticed that in Figure 3(a), there are large heterogeneous areas. Figure 4 shows the auto-detected heterogeneous areas which are depicted as the cyan blocks. Figure 4(a) is the result of the first division without shift and Figure 4(b) is the result of the second division with a half scale shift. Figure 5 is the heterogeneous areas combining two "LR" data, i.e. the result of Figure 4(a) and Figure 4(b). They are demonstrated as cyan areas. Obviously,

the heterogeneous areas in Figure 5 is more accurate. Figure 6 gives a comparison of the radiometric normalization before and after excluding heterogeneous areas using the above processing flow of radiometric normalization. Figure 6(a) and Figure 6(b) are the result of Figure 3(a) and Figure 3(b) before excluding heterogeneous areas; Figure 6(c) and Figure 6(d) are the result after excluding heterogeneous areas. Obviously, by excluding the heterogeneous areas, the effect of radiometric normalization is improved.



Figure 3. Images for radiometric normalization

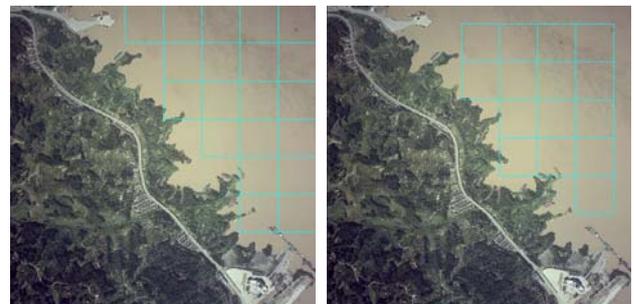


Figure 4. Auto-detected Heterogeneous areas



Figure 5. Heterogeneous areas combining two "LR" data



Figure 6. Comparison of radiometric normalization

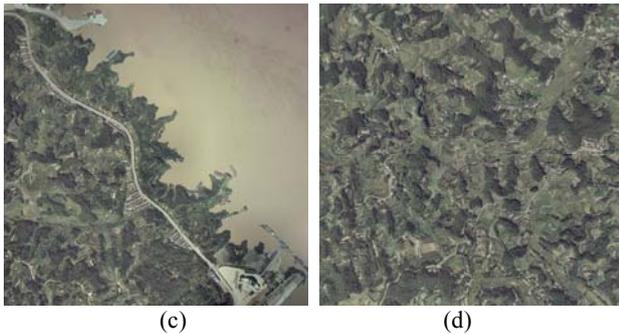


Figure 6. Comparison of the radiometric normalization before and after excluding heterogeneous areas

4. CONCLUSION

This paper based on the idea of SR proposals an auto-detection method for heterogeneous areas using texture information. It divides the image twice using the given scale. The second division has a half scale shift compared to the first division. Then based on the two detected results from the twice division, this paper uses the SR reconstruction method to achieve heterogeneous areas with higher “resolution”. When getting heterogeneous areas, it is available to exclude them during the generation of statistics for the radiometric normalization. It can be noticed that the detected heterogeneous areas are not so accurate and still limited by the given scale. But the undetected heterogeneous areas are small which have very small effect on the radiometric normalization, and the presented approach gives a rapid solution to detect the heterogeneous areas automatically, i.e. it achieves a good efficiency at the cost of very little effect. Experiments validate the processing effect of the proposed algorithm and indicate that the approach proposed by this paper is feasible and can improve the effect of radiometric normalization obviously.

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