Relative radiometric normalization of H-res multi-temporal thermal infrared (TIR) flight-lines of a complex urban scene

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Abstract

Useful biophysical information such as surface temperature and surface energy flux provided by thermal infrared (TIR) remote sensing sensors are commonly used for studying urban temperature variations and urban heat islands. However, an important limitation of TIR imagery is the influence of local microclimatic variability (i.e., wind, precipitation and humidity) on sensor observations. This can cause the same scene components (e.g., roads and buildings) to exhibit different thermal states (i.e., temperatures) when exposed to varying microclimate conditions. In the case of airborne TIR imagery, the ambient sensed temperature also naturally changes between flight line acquisitions, resulting in an image mosaic with different temperatures for the same scene components, making detailed analysis non-trivial.

In an effort to mitigate this problem and to produce a 'seamless' TIR scene mosaic, we evaluate three different relative radiometric normalization methods on two adjacent flight-lines of TABI-1800 data (each ~35km x 0.9km, at 50 cm spatial resolution, and 0.05 °C thermal resolution) that were acquired in May 2012 over The City of Calgary, Alberta, Canada. We then describe their effects on the resulting mosaic. The evaluated methods include: (i) Histogram Matching, (ii) Linear Regression based on Pseudo Invariant Features (PIF), and (iii) Theil-Sen Regression based on PIF. Based on visual assessment, results show that *Histogram Matching* produces is the *best*. Such radiometric normalization (i) increases the visual agreement between the thermal airborne flight lines, (ii) produces a seamless mosaic, (iii) improves radiometric agreement, (iv) improves hot-spot detection, and (v) provides accurate data for thermal-based energy models.

Background and Relevance

While thermal remote sensing provides important biophysical information (i.e., temperature and surface energy flux) about the earth's surface, the applicability of these data still remains challenging due to difficulty in calibration and appropriately identifying atmospheric attenuation (Quattrochi and Luvall, 1999). In the case of urban surfaces, additional challenges are imposed by the composite and heterogeneous nature of the surface itself, as well as the surrounding environment (Voogt and Oak, 1997). Therefore, to use thermal remote sensing data to accurately measure urban thermal characteristics, it is necessary to thoroughly understand the limitations of such data. Furthermore, current satellite platforms only acquire moderate to low resolution (60 m to 1 km) thermal imagery that are not suitable for detailed thermal mapping of urban surfaces. As a result, airborne TIR imagery are increasingly used for urban mapping exercises (Hay et al., 2011; Weng, 2011). However, to thermally mapping large urban areas at a high spatial resolution (~1m), airborne imagery need to be acquired in numerous flight lines and mosaiced together; which induces geometric and radiometric variations between flight paths (Rahman et al., 2012). Due to these radiometric differences, the same class of scene objects tend to exhibit different spectral characteristics within a single mosaic, making image analysis and classification difficult (Tuominen and Perkkarinen, 2004).

In an effort to reduce similar concerns, *relative radiometric normalization* techniques have been used for decades to normalize multitemporal multispectral remote sensing data (Salvaggio, 1993; Hall et al., 1991; Schott et al., 1988). However, the applicability of these techniques on multitemporal thermal datasets has yet to be adequately assessed. With the increased demands for thermal data by the remote sensing community (Hay et al., 2011), we recognize an emerging need to evaluate the applicability of relative radiometric normalization techniques on high spatial resolution (H-res) TIR imagery. Based on these ideas, this paper focuses on the evaluation of three different relative radiometric normalization techniques applied to a H-res TABI-1800 (Thermal Airborne Broadband Imager) dataset collected over a portion of the City of Calgary in May 2012.

Methods and Data

Our study area is located in the west part of the City of Calgary, Alberta Canada, and represented by two flight lines of TABI-1800 imagery (each ~0.9 km wide x 35 km long at 50 cm spatial resolution) acquired at night (01:00 to 02:00) on May 13, 2012. The TABI-1800 is an airborne thermal camera developed by ITRES Research Limited (2012) with a swath width of 1,800 pixels (FOV: ±20°) in the 3.7- 4.8 µm spectral region, a thermal resolution of 0.05 °C, and the ability to collect up to 175 km^2 per hour at 1.0 m spatial resolution. In ideal conditions, each TABI-1800 flight line is also acquired with a 30% overlap between adjacent flight lines. This dataset was collected from an average altitude of 1250 m above ground level and a corresponding digital terrain model (10 m spatial resolution) was used to orthorectify the imagery and correct for elevation based thermal gradients.

In order to radiometrically normalize two adjacent thermal flight lines, we apply three radiometric normalization algorithms from the literature that are typically used to correct multispectral imagery (Hall et al., 1991). These include: (i) Histogram Matching, (ii) Linear Regression based on Pseudo Invariant Features (PIF), and (iii) Theil-Sen Regression based on PIF. In each case, the first flightline is considered the *master* image and the second flightline as the *slave*. The slave is then normalized to the master image so that it appears as if they were collected at same time, under the same atmospheric/microclimatic conditions.

Histogram Matching is defined as a linear shift of the slave histogram to the master histogram based on the mean difference[1] (Richards, 2005). To implement this method, we first calculate the mean difference of the overlap sections (between the master and the slave images) and then shift the slave histogram (derived from the entire image - not just the overlap) to the master histogram, based on the calculated mean difference.

It has been argued that the spectral properties of some features (such as soil and seasonal vegetation) rapidly change over time, consequently the use of these features as references for the radiometric normalization of multitemporal images may introduce errors. To mitigate these errors, Salvaggio (1993) and Schott *et al.* (1988) suggested using *pseudo invariant features* (PIFs) as references for radiometric normalization as these features are expected to provide a consistent radiometric response over time. To perform a PIF-based radiometric normalization, we closely examined the overlap portions of the master and the slave images and manually selected 30 samples of three types of (pseudo invariant) land cover. 10 samples were then collected for each of the three cover types: (i) grass (cool), (ii) road (hot) and (iii) water (in-between temperature). Next, the average DN values within the samples found in the slave image are then plotted against those of the master image so that they fit two different types of regression techniques: (i) Linear regression, and (ii) Theil-Sen regression.

Linear regression normalization is based on the assumption that the atmospheric differences between images of the same geographic location, but collected at different times, are linearly correlated (Schott *et al.*, 1988; Hall *et al.*, 1991). To perform a PIF-based linear regression, the

[1] The mean difference is a measure of dispersion between two independent datasets

average DN values of the PIFs are scatter plotted and a linear regression equation is fitted to this point cloud. The corresponding regression equation is then applied to the entire slave image to radiometrically normalize it to the master image.

The Theil-Sen regression model uses the median of pairwise slopes as an estimator of the slope parameter for the correlation between two datasets (Peng *et al.*, 2008). The pairwise slopes are calculated for the same 30 pairs of PIFs previously mentioned and the median slope is then computed. Next, the median slope value and the median of the pixel values of the PIFs from the master and the slave are introduced into a linear equation to calculate the y-intercept. The resulting median slope and the y-intercept forms the T-S linear regression equation. This equation is then used to radiometrically normalize the slave image to the master image.

Results

To visually compare these results, each normalized slave image is individually mosaiced with the master image and the features along the mosaic join line are assessed. Visual interpretation reveals that most of the methods exhibit improvement over simply joining the raw datasets. However, the magnitude of improvement is different according to the method used and the type of ground targets assessed.

For example, Figure 1 displays a portion of grassland along the mosaic line showing that all the applied radiometric normalization techniques improve over the raw join (Figure 1A). However, the Histogram Matching method (Figure 1B) produces a mosaic join that is essentially seamless.

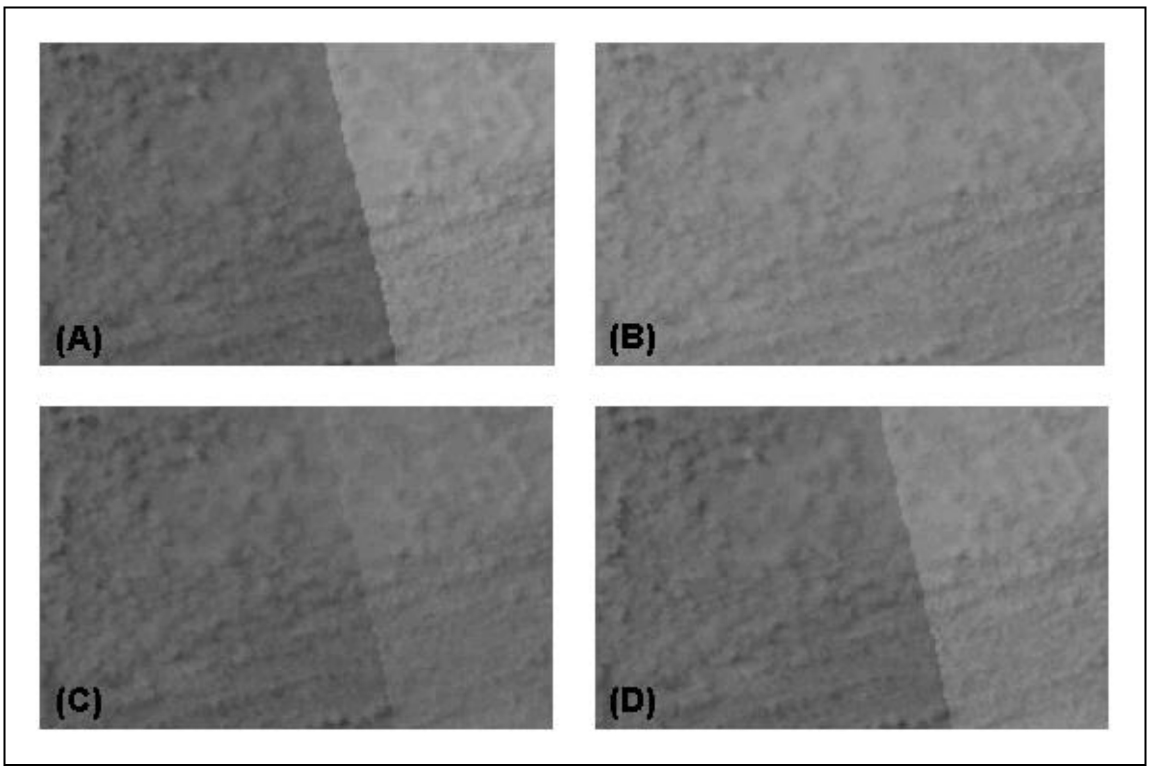

Figure 1: A comparison of three different radiometric normalizations of the cover type *grass*: (A) Raw images, (B) Linear Histogram Matching, (C) PIF-based Linear Regression, (D) PIF-based TS Regression,

In a second example we examine a portion of a road (Figure 2) where we notice that again the Histogram Matching method performs very well, with a barely visible join line (Figure 2B). However, the PIF-based TS regression method (Figure 2D) dramatically decreases the visible radiometric agreement between the master and the slave images for this land cover class.

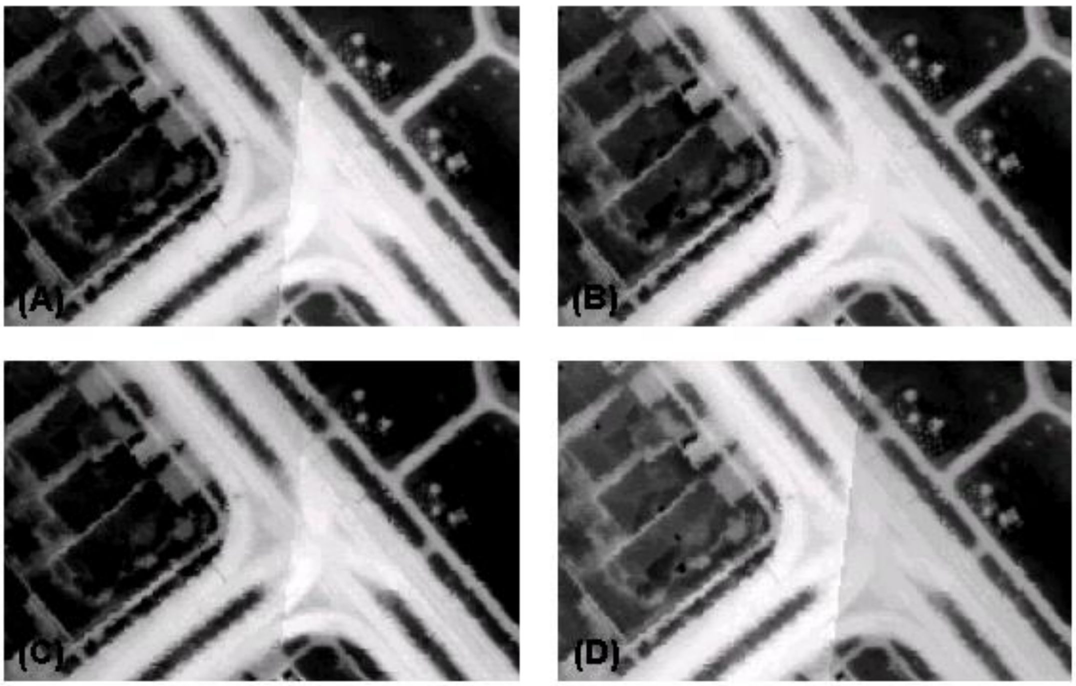

Figure 2: A comparison of four different radiometric normalizations of the cover type *road*: (A) Raw images, (B) Linear Histogram Matching, (C) PIF-based Linear Regression, (D) PIF-based TS Regression

Conclusions

Three radiometric normalization techniques commonly applied to multispectral images are used to radiometrically normalize a very high resolution TIR dataset. Except for T-S regression, all other evaluated methods reveal an improved radiometric agreement between the master and the slave image. Visually, the best result is achieved from Histogram Matching, which is also the simplest and computationally fastest method. The manually selected PIF-based linear regression method also improves the agreement between the master and the slave images when compared to the raw image. However, the manual selection of features makes PIF-based methods time consuming and this will grow as the number of flight lines to be radiometrically normalized increases. Of all the methods evaluated, Theil-Sen regression is observed to be the most unsuitable for normalizing H-res TABI-1800 imagery. As shown in some cases it actually further visually decreased the radiometric agreement of specific classes shown in both the master and the slave images.

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