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Detecting tents to estimate the displaced populations for post-disaster relief using high resolution satellite imagery

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ABSTRACT

Estimating the number of refugees and internally displaced persons is important for planning and managing an efficient relief operation following disasters and conflicts. Accurate estimates of refugee numbers can be inferred from the number of tents. Extracting tents from high-resolution satellite imagery has recently been suggested. However, it is still a significant challenge to extract tents automatically and reliably from remote sensing imagery. This paper describes a novel automated method, which is based on mathematical morphology, to generate a camp map to estimate the refugee numbers by counting tents on the camp map. The method is especially useful in detecting objects with a clear shape, size, and significant spectral contrast with their surroundings. Results for two study sites with different satellite sensors and different spatial resolutions demonstrate that the method achieves good performance in detecting tents. The overall accuracy can be up to 81% in this study. Further improvements should be possible if over-identified isolated single pixel objects can be filtered. The performance of the method is impacted by spectral characteristics of satellite sensors and image scenes, such as the extent of area of interest and the spatial arrangement of tents. It is expected that the image scene would have a much higher influence on the performance of the method than the sensor characteristics.

Introduction

Due to fast onset disasters (earthquakes, floods), slow onset disasters (droughts), or conflict (armed conflict, violence, or human rights violations), and other protracted crises in various parts of the world, the number of refugees and internally displaced persons (IDP) is rapidly increasing (Land et al., 2010). The United Nations High Commissioner for Refugees (UNHCR), the United Nations agency responsible for refugees, reported approximately 42 million forcibly displaced people worldwide at the end of 2008 (UNHCR, 2009). The Darfur conflict caused the largest refugee/IDP population, accounting for about 3 million people by January 2009 (UNHCR, 2009). Refugees need essential facilities such as tents for survival and it is therefore key to accurately estimate the number of refugees to plan and manage efficient relief operations. Refugees usually gather in camps where essential facilities for survival are provided. Refugee camps are often maintained through the continued support of the donor community and can be in place for many years. The tents in camps are primarily used for shelter for refugees and can thus be used to estimate refugee numbers. Consequently, accurate estimates of refugee numbers can be inferred from the number and size of the tents (Giada et al., 2003).

There are various ways to count tents. One way is to get information from organizations who host the camps and setup the tents. This way is simple. However, the information belongs to different international organizations and local organizations such as local government, and is thereby sparse and difficult to access. Also due to limitations in administrative capacity, the information cannot always be updated in time, especially in developing countries (i.e., countries with lower administrative capacity), and it is therefore difficult to obtain the up-to-date information about tents. The typical way to count tents is *in situ* assessment. The method can obtain detailed information about the tents, such as whether or not they are occupied. However, *in situ* assessments of the number of tents (and therefore, the number of refugees) are time-consuming, costly, and subject to the limitations in administrative capacity noted above.

Using remote sensing imagery to estimate refugee numbers has recently been advocated (UNHCR, 2009; Wu and Murray, 2007; Giada et al., 2003; Chen, 2002; Harvey, 2002a, b; Webster, 1996). There are two main categories of methods. One is to develop a so-called zonal model or pixel-based model to estimate population

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(Webster, 1996; Chen, 2002; Harvey, 2002a, b; Wu and Murray, 2007). In these models, the population indicators, such as spectral radiance and land use/land cover, are extracted from remote sensing imagery to estimate the camp population, and it is not necessary to identify the tents. However, the population indicators in these models are not directly related to housing information and the models are difficult to validate and compare (Wu and Murray, 2007), so new approaches are still needed. Lo (1989, 1995) suggested that a more accurate method for refugee population estimates should be based on the average number of refugees per tent, highlighting the significance of accurately detecting tents. The potential for using high resolution remote sensing imagery to extract tent information for estimating refugee numbers is increasingly recognized (Brown et al., 2012; UNHCR, 2009; Giada et al., 2003), mainly due to the availability of very high spatial resolution satellite sensors such as GEOEYE-1, Ikonos-2, QuickBird, Orbview-3, IRS-P6, and EROS A&B (Bjorgo, 2000a), as tents are typically small (the area ranges from 6 m^2 to 60 m^2). In general, tent-related information extracted from satellite imagery is often carried out by visual interpretation (Brown et al., 2012; Giada et al., 2003; Bjorgo, 2000b). Visual interpretation of tents from high resolution satellite imagery is accurate but time-consuming and labor intensive, limiting its application for relief operations following a disaster. Because successful appropriate policy needs up-to-date information to ensure the appropriate allocation of resources to the affected population, an automated method, which can quickly and accurately provide the tent information from high resolution satellite imagery, would be valuable. However, little research has been conducted in this area. Giada et al. (2003) used four methods to detect the refugee tents at Lukole refugee camp in Tanzania: pixel-based supervised classification, unsupervised classification, mathematical morphology, and object-based segmentation and classification. Comparing the performance of these four methods, they found that mathematical morphology and object-based segmentation and classification performed better than pixel-based supervised classification and unsupervised classification. Because object-based segmentation and classification needs more prior-knowledge than mathematical morphology and has to set a series of complex rules (Land et al., 2010; Benz et al., 2004), mathematical morphology is preferred practically. In the mathematical morphology method, the determination of the morphology threshold is critical to detect the target tents (Soille, 1999). Giada et al. (2003) selected 40% for the upper and 25% for the lower intensity values as the thresholds in their study. To avoid the subjectivity in determination of the morphology threshold, and to automatically identify the tents from high resolution remote sensing imagery, we present an easily implemented automated mathematical morphology method, in which a threshold function is addressed, to generate a camp map from which one can estimate the affected population through counting tents. We demonstrate its performance in detecting tents, and thereby in estimating the refugee numbers, in Ban Nam Khem in Thailand and Van in Turkey.

Methods and materials

Study area

Two camps were selected as study areas: Ban Nam Khem in Thailand and Van in Turkey (Fig. 1). Ban Nam Khem was a small fishing village located north of Khao Lak on the Andaman coast. On the morning of 26 December 2004, an undersea earthquake of magnitude 9.0 on the Richter scale triggered a devastating tsunami that affected many countries with shores on the Indian Ocean. Thailand was one of the hardest hit countries among the affected countries. In Ban Nam Khem, the entire village was badly damaged; only a few buildings were left standing. Over 3000 people were lost and up to 80% of infrastructure, including the fishing fleet, harbor, and fish processing facilities, were damaged (UNDP, World Bank and FAO 2005; Brown et al., 2008). Following the tsunami the Ban Nam Khem School was used as the main refugee camp which was a relatively large and sophisticated and had facilities for housing, cooking, and sanitation, and services to support livelihood and physiological recovery. The Ban Nam Khem School was chosen as area of interest (AOI).

The satellite image for Ban Nam Khem School was acquired from the Ikonos satellite on 2 March 2005. Ikonos orbits at an altitude of 681 km, at an inclination of 98.1° and is sun-synchronous. The panchromatic band used (0.45–0.90 μm) has a spatial resolution of 1 m. It covered an area of 484 m by 323 m centered on longitude 98°16′33″ North and latitude 8°51′32″ East. The image was geometrically corrected to the UTM Zone 47 N (WGS 84) map projection by the data provider.

At 13:41 (local time) of 23rd Oct 2011, a magnitude 7.2 earthquake occurred in the Van province in Eastern Turkey. The shallow but powerful earthquake was centered near the city of Van which was close to the border with Iran, with the greatest destruction occurring in the nearby town of Ercis which had population of 75,000. In the aftermath of the earthquake, more than 2000 buildings were destroyed, among which more than 100 buildings collapsed at Ercis. The AOI is centered on longitude 38°31′5″ North and latitude 43°20′1″ East, covering an area of 381 m by 319 m. The satellite image for the AOI of Van was acquired from GEOEYE-1 satellite on 9th January 2012. GEOEYE-1 orbits at an altitude of 684 km, at an inclination of 98° and is sun-synchronous. The panchromatic band used (0.45–0.80 μm) has a spatial resolution of 0.5 m, and is geometrically corrected to the UTM Zone 38 N (WGS 84) map projection by the data provider.

Methods

Mathematical morphology is used to extract tent information in the camp. Mathematical morphology is especially useful in detecting objects which have a clear shape, size, and spectral contrast. Tents are more or less rectangular objects, have an area between roughly 6 and 60 m^2 and always show brighter than their surroundings in panchromatic images because they have higher reflectance. Due to these characteristics, it is reasonable to employ mathematical morphology to detect tents in camps. We use a morphological chain of operators, which includes morphological opening, opening by reconstruction, top-hat by reconstruction, and morphological threshold, to detect tents in camps (Fig. 2) (Giada et al., 2003; Soille, 1999; Serra, 1982). Mathematical morphology is based on set theory and here we only introduce the knowledge related to these four morphology operators. For a more detailed mathematical background, please refer to Soille (1999) and Serra (1982). Given the gray-scale image A, a structuring element S, and pixel location in image (x, y), the morphology opening is

$$\psi_s(A) = (A \Theta S) \oplus S \tag{1}$$

where θ is morphology erosion and $\oplus$ is morphology dilation. These are two basic morphological operators among which morphology erosion identifies the minimum value of image A from all values of A in the region coincident with S, whereas morphology dilation identifies the maximum value of image A from all values of A in the region coincident with S.

The opening by reconstruction of size n of an image A is defined as the reconstruction by dilation of A from the erosion of size n of A. That is,

$$O_R^{(n)}(A) = R_A^D[(A \Theta nS)] \tag{2}$$