Commercial Remotely Sensed (CRS) Data

Natural disasters can severely impact transportation networks. In the hours and days following a major flooding event, knowing the location and extent of the damage is crucial for incident managers for a number of reasons: it allows for emergency vehicle access to affected areas; it facilitates the efficient rerouting of traffic; it raises the quality and reduces the cost of repairs; and it allows repairs to be completed faster, in turn reducing the duration of costly detours. Commercial Remote Sensing (CRS) imagery is increasingly being used in disaster response and recovery, but acquiring imagery is far easier than extracting actionable information from it. An automated approach to damage assessment is needed, but traditional automated image analysis techniques are inadequate for identifying or characterizing road and bridge damage from high resolution imagery. We propose a project with two objectives: 1) to develop, calibrate and deploy a decision support system capable of identifying road and bridge damage from high-resolution commercial satellite images and; 2) to estimate the amount and type of fill material required for repairs using digital surface models derived from lightweight Unmanned Aerial Vehicles (UAV) programmed to fly over damage road segments. This approach would employ state-of-the-art, object-based image analysis techniques, cost-based image matching, and other advanced computing techniques. We also propose to collaborate with state departments of transportation to develop a web-based interface to share information derived from the CRS imagery.

As high resolution has become more prevalent, it has opened up great possibilities for automated detection of fine-resolution features. Commercial remotely sensed (CRS) data has grown in importance as a resource for planners and decision makers, particularly since the IKONOS-2 satellite became operational in 1999. The latest generation of commercial satellite systems, such as WorldView-2 and GeoEye-1, offer sub-meter resolution imagery with revisit times of 1-3 days. Lightweight Unmanned Aerial Vehicles (UAV), such as the Gatewing, can be deployed in a matter of minutes, fly low enough so as to avoid needing Federal Aviation Administration Approval (FAA), and capture highly accurate centimeter-resolution stereo imagery.

CRS plays a growing and important role in disaster response. During major disasters the International Charter (http://www.disasterscharter.org) is activated. The International Charter is a consortium of government agencies (e.g. NOAA) and CRS companies (e.g. GeoEye). A typical activation of International Charter allows organizations involved in disaster response and recovery access to all CRS data acquired in support of the event. The USGS makes the data available via its Hazard Data Distribution System (HDDS) (http://hdds.usgs.gov/hdds2/). In the days following Hurricane Irene in Vermont over 300 CRS scenes were acquired, totaling over 500GB worth of data. Both of the major US-based CRS companies, DigitalGlobe and GeoEye, participate in the International Charter.

Organizations, such as the Department of Defense, who specialize in damage assessment still primarily employ manual interpretation techniques such as those covered by Kienegger (1992) (United States Army, 2009). Such approaches, while achieving high levels of accuracy this can be extremely time consuming and costly. State transportation departments simply do not have the personnel with either the time or the expertise to handle the vast amounts of CRS satellite imagery that become available following a disaster. In short, interpret massive amounts of imagery is both prohibitive from both a cost and human resource perspective.

Automated classification algorithms long held the promise of saving both time and money. Since the inception of digital remote sensing in the 1970s the most common method for automating the extraction from CRS satellite imagery has been the so-called pixel-based approach. This process is vastly different than manual interpretation. Humans make use of not only the spectral (tone) information in an image, but also the geometric, textural, and contextual information. Pixel-based approaches have come under increased scrutiny due to the relative poor accuracy of the resulting classification when compared to manual interpretation (Olson, 2009). Numerous studies have found pixel-based approaches unsuitable for the latest generation of high-resolution multispectral imagery, particularly in heterogeneous landscapes like urban environments (Chen et al., 2004; Cushnie, 1987; Kontoes et al., 2000; Thomas et al., 2003; Zhou and Troy 2008). Although some advances have been made by incorporating texture into the image classification process (Gong and Howarth, 1990; Puissant et al., 2005) in heterogeneous landscape such as urban areas, the classification accuracy of textural analysis is still relatively low (Chen et al., 2004).

In the case of detecting roadway damage, the pixel-based approach is particularly unsuited because the damaged area is unlikely to have any sort of unique spectral signature. Damage to a road or bridge will be composed of pixels with a wide variety of reflectance values, and many of those reflectance values will be similar to those of pixels of features that are not damage (Figure 1). Furthermore, subtle shifts in the location of pixels between pre- and post-even CRS imagery make pixel-based approaches, which require precise co-registration entirely unsuitable. Damage to roads and bridges is identified using a combination of spectral, textual, geometric, and contextual information from two sets of imagery that likely have minor georegistration errors. Any automated approach to detecting damage must account for these factors.

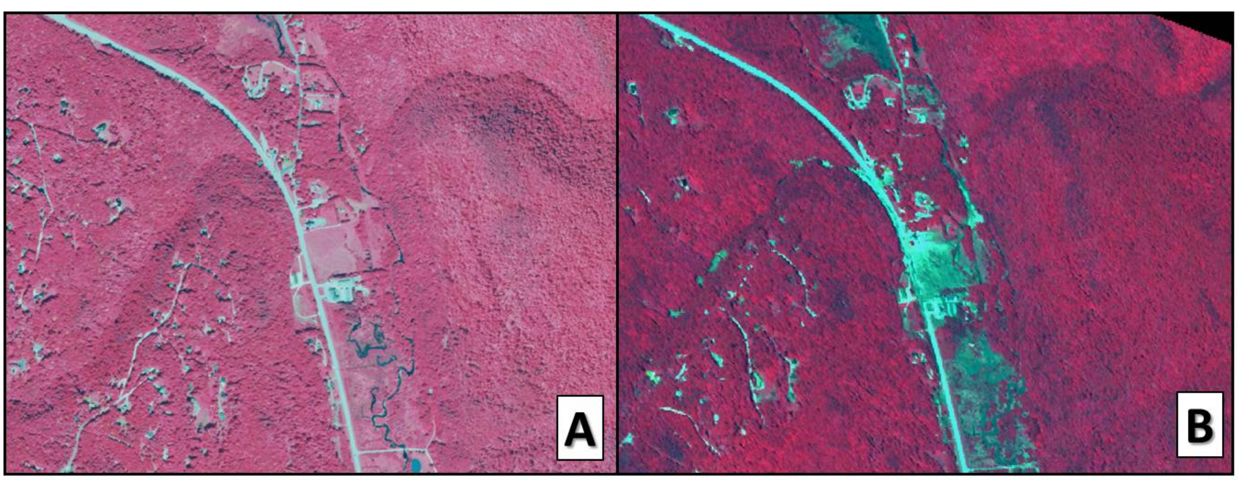

Figure 1. Images of Route 100 in Vermont both pre (A) and post (B) Hurricane Irene. The pixels for the damaged area in the center of (B) have no distinct spectral signature, and many are practically spectrally identical to other paved surfaces or the silt-laden water.

To deal with the complexities of high-resolution imagery with pixel sizes that are frequently smaller than real-world objects (e.g. half meter), an automated approach must classify objects rather than pixels (Blaschke, 2010; Walker and Blaschke, 2008). Object-based image analysis (OBIA) has emerged as the most promising and widely used technique to the automated extraction of information from high-resolution CRS imagery. OBIA, which attempts to replicate aspects of human cognition, allows spectral, geometric, and contextual information to be brought into the feature extraction process, overcoming the limitations of pixel-based approaches (Hay and Castilla, 2006). OBIA techniques also provide a framework for the direct integration of thematic GIS data sets (e.g. roads), and can be built on top of expert systems that can be designed in such a way that they are flexible enough to adjust to differing sensors and image characteristics (Smith and Morton, 2010). Expert systems also have the advantage that they do not inherently require “training data,” for each run, something that is difficult to obtain during a crisis situation (Buchanan, 1983). OBIA techniques have repeatedly shown to be a robust and accurate approach to feature extraction (Geneletti and Gorte, 2003; Laliberte et al.,

2004; Shackelford and Davis, 2003). OBIA approaches been found to be an excellent method for classifying even fine-scale objects such as individual trees, houses, and driveways (Troy and Zhou, 2007; Zhou and Troy, 2008) (Figure 2).

Figure 2. Example output from of a feature extraction for Syracuse, NY developed by the proposal team. OBIA techniques were applied to high-resolution CRS data to extract both natural and man-made features with over 94% accuracy.

OBIA's greatest strength is its ability to incorporate contextual information that permits feature extraction from local (e.g. neighborhood), semantic, cultural, geometric, and geographic relationships (Divvala et al., 2009) (Figure X). OBIA techniques also provide a way to overcome the limitations associated with existing vector and raster data models. Data fusion OBIA approaches data have been successfully used to identify roadways (Hinz and Baumgartner, 2003), land use (Ban et al., 2010), and buildings (Tullis and Jensen, 2003). In a OBIA workflow, segmentation algorithms are used to group pixels into objects. Like pixels, image objects have spectral properties (mean band values), but unlike pixels they have spatial (shape, size, texture) characteristics and are topologically aware (i.e., each object "knows" its neighbor objects). Image objects can also be organized hierarchically to reflect relationships between sub- and super-objects.