AUTOMATED DETECTION OF PEOPLE AND VEHICLES IN NATURAL ENVIRONMENTS USING HIGH TEMPORAL RESOLUTION AIRBORNE REMOTE SENSING

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ABSTRACT

Advances in aerial platforms, imaging sensors, image processing/computing, geo-positioning systems, and wireless communications make near real-time detection and tracking of moving objects on the ground more practical and cost effective. In Coulter et al. (2011), we presented a methodological framework for near real-time monitoring of border areas with active and frequent illegal immigration and/or smuggling. The patent pending methodology is designed to assist law enforcement in locating and monitoring people and/or vehicles traversing the border region. The approach utilizes low cost platforms such as light aircraft (LA) or unmanned aerial systems (UAS) for repeat imaging over short time periods of minutes to hours depending on the border response zone (i.e. urban, rural, and remote). Specialized image collection and preprocessing procedures are utilized to obtain precise spatial co-registration between multitemporal image frame pairs. In addition, specialized change detection techniques are employed in order to automate the detection of people and vehicles moving within the border region. The objective of this paper is to describe the specialized techniques and provide initial results for detecting people and vehicle object changes in the context of U.S. border security. However, detection and tracking of moving objects across wide geographic areas may also be appropriate for such things as search and rescue of missing persons, wildlife tracking, and monitoring military resources or enemy movements on the battlefield. This work is developed by the National Center for Border Security and Immigration: A Department of Homeland Security Science and Technology Center of Excellence.

KEYWORDS: wide area surveillance, change detection, automated, real-time, sensor orientation, airborne, UAV, UAS, border security

INTRODUCTION

The U.S. Customs and Border Protection (CBP) agency is responsible for securing the borders of the United States, and the Border Patrol specifically is responsible for patrolling the 10,000 kilometers of Mexican and Canadian international borders. Their general mission is to detect and prevent illegal entry of people and/or goods into the United States. The Border Patrol also performs a humanitarian mission, by rescuing people lost in remote locations and exposed to harsh environmental conditions. Since the terrorist attacks of September 11, 2001, the focus of the Border Patrol has expanded to include detection, apprehension and/or deterrence of terrorists and terrorist weapons. It is not practical, however, to closely monitor the tens of thousands of square kilometers of open land within close proximity of the border using agents and ground-based sensors alone. Airborne remote sensing offers the potential to monitor expansive areas within the border region, and identify activity of people/vehicles that has not been detected by agents patrolling the border or by ground-based sensors.

The Border Patrol's National Border Strategy document (Office of Border Patrol, 2004) calls for 1) improved detection strategies, 2) expanded sensing platforms, including unmanned aerial systems (UAS), and 3) increased rapid response capabilities through means such as the addition of aviation assets capable of light observation, medium lift, or fixed-wing flight. As part of the National Center for Border Security and Immigration (NC-BSI or BORDERS), San Diego State University (SDSU) and its business partners are developing and producing low cost remote sensing techniques and systems that can aid the Border Patrol in their mission. The vision of this project is to have light aircraft (LA) and/or UAS patrolling active border regions, collecting repeat-pass imagery over periods of minutes, identifying changes in the imagery that are associated with the movement of people and/or vehicles through the border region, and providing that information in a timely manner to agents on the ground. Agents may then utilize the information to initiate interdictions and locate individuals of interest.

Near Real-time Change Detection

Advances in microprocessors and communication technology have enabled advances in automated image processing and retrieval such that semi-automated monitoring of transient and dynamic phenomena is now possible using remote sensing (e.g., Herwitz et al., 2003; Stryker and Jones, 2009, Davies et al., 2006; Ip et al., 2006). While the identification of appropriate sensors and platforms is critical to any remote sensing problem, the appropriate and timely processing of image data retrieved from those sensors represents the primary challenge to deploying remote sensing technologies to address time-sensitive information requirements (Joyce et al., 2009).

Near real-time change detection for border monitoring may be performed by collecting repeat-pass imagery over periods of minutes to hours using an aircraft flying a defined (e.g., racetrack) flight pattern. There are five basic steps for near real-time change detection: (1) collect multitemporal imagery using specific techniques that enable precise spatial co-registration of multitemporal images; (2) spatially co-register the multitemporal images; (3) perform change detection to identify features of interest that are newly apparent or have moved locations; (4) collect geographic coordinate information about the features of interest; and (5) transmit the locations of change features of interest (as well as any relevant attributes) to command and control stations on the ground. Near real-time change detection will allow agents to see images of detected changes on their computer screens as they are detected, and to instantly identify the locations of these features of interest on a map. Further, images with detected changes can be compared to previous images to further understand the type and nature of detected changes.

Methods for collecting and spatially co-registering multitemporal airborne imagery with high precision are described in Coulter et al. (2003), Stow et al. (2003), Coulter and Stow (2005), Coulter and Stow (2008), and Coulter et al. (2011). Further, SDSU is developing software tools for automating the spatial co-registration of multitemporal image pairs. Use of such imagery enables the detection of very small changes between multitemporal image sets (Stow et al., 2008; Coulter and Stow, 2009). Here we describe specific image processing techniques for automated detection of people, vehicles, and other objects of interest moving across undeveloped landscapes.

BACKGROUND

Airborne Image Resolution for Near Real-time Change Detection

Remotely sensed imagery can be characterized by four types of resolution: 1) spatial, 2) spectral, 3) radiometric, and 4) temporal. Each type of resolution can affect the type or utility of information that may be extracted from the imagery. In the case of change detection, resolution can affect the types of changes that may be detected and the quality of change detection products.

Spatial resolution refers to the finest spatial distance over which one feature may be discriminated from the next in remotely sensed imagery. Spatial resolution generally refers to the ground resolution element, which is the ground distance covered by a single image pixel. Spectral resolution refers to the number and spectral characteristics (spectral region and spectral range) of different wavelengths of energy from the electromagnetic spectrum that may be discriminated. Increased spectral resolution can enable a greater number of features within the scene to be discriminated based upon their spectral reflectance or color (in the case of visible light). Radiometric resolution refers to the capability of an imaging system to distinguish different magnitudes of energy from the electromagnetic spectrum. Increased radiometric resolution offers increased ability to discriminate features in areas of shadow and features which are very similar in terms of reflectance response. Temporal resolution refers to the frequency with which multitemporal imagery is collected.

For the detection of people and vehicles within the border region, we have tested imagery with varying spatial resolutions and recommend an image spatial resolution between 3-6 inches (0.08-0.15 m). This range of spatial resolution provides sufficient detail to automatically detect and visually identify changes associated with people and their shadows. Given the trade-off between image spatial resolution and extent of ground coverage per frame, medium to large format digital cameras with imaging arrays at least 5000 by 3000 pixels are recommended to increase the ground coverage per frame.

Commercial-off-the-shelf (COTS) camera systems sensing visible (blue, green, and red) light may be used for near real-time detection. Full resolution images with minimal to no compression should be captured and utilized for change detection to maximize the potential fidelity of the imagery and the detail with which changes may be detected. In addition, it is important to note that pan-sharpening and/or subsampling of measured response on Bayer array charge coupled devices (CCD) will reduce image quality and change detection accuracy (Thomas et al., 2008; Stow et al., 2009).

There are many factors to consider when determining the frequency (temporal resolution) with which multitemporal imagery is collected for near real-time change detection. These include: 1) the location being monitored (distance from urban areas or pick-up sites, travel times due to land cover/terrain characteristics, etc.), 2) the acquisition rate of the platform/sensor combination that is being used (what is the imaging swath and aircraft velocity), and 3) the costs of operating the airborne image-based monitoring system. Ideally, imagery for near real-time change detection would be collected frequently enough that moving objects would not be missed between imaging passes and scene conditions (reflectance characteristics and vegetation/rock/terrain shadows) would change very little between repeat image passes (minimizing false change detections). Imaging at regular time intervals ranging from every 15 minutes to every 30 minutes is expected to be appropriate for change detection in a border monitoring context.

Imaging sensors with 8-bit radiometric resolution are sufficient for near real-time change detection, as brightness changes associated with shadows, clothing, and vehicles may be discriminated using 8-bit imagery. Imaging sensors with higher (e.g., 11-bit) radiometric resolution may be utilized for increased discriminating between brightness values. However, image file sizes will double (since 11-bit data is stored using 16-bit files) and automated, on-board processing speeds may be reduced which has the potential to affect the timeliness of change detection product delivery to command and control stations. If there is a negative effect on near real-time change detection, then the advantages and disadvantages of using 11-bit imagery will need to be weighed. .

Image Collection

Continuous, long duration image-based monitoring of portions of the border will require one or more low-cost systems, the number of which is dependent on platform speed, sensor swath, the width of border region to be monitored, and the required monitoring interval. Each system will acquire imagery by flying a consistent pattern that requires a specific amount of time to complete. For example, a single aircraft may fly two parallel flight lines in a racetrack pattern, where the first line is flown east to west, the aircraft turns around, and the second flight line is flown west to east. This pattern would be repeated continuously, and the time for the aircraft to return to any photo station along the path would be on the order of 15-30 minutes. Monitoring of areas larger than those covered by the two flight lines (for example) would necessitate additional aircraft imaging in a similar manner.

Traditional remote sensing platforms (i.e., satellites or fixed wing aircraft) and sensor technologies (e.g., large format digital sensors, film based aerial mapping cameras, and line scanners) require significant hardware and human resources to operate. Manned LA and small to medium sized UAS (Figures 1) represent viable data acquisition alternatives to traditional, large manned aircraft at significantly reduced relative cost (Laliberte et al., 2010). Some UAS permit extended flight times (>12 hours) and coverage without putting human lives at risk. Their operation in the National Airspace System, however, remains restricted under the current Federal Aviation Administration (FAA) regulatory environment. LA have fewer operating restrictions than UAS, and may operate in more diverse weather conditions (e.g., higher winds). In the near term (e.g., 5-10 years), LA represent a viable choice. However, the extended duration, automated repeatability, and relatively small resource footprint of UAS may eventually make them the platform of choice for remote sensing based monitoring.

Both LA and UAS platforms are ideally suited for the deployment of a variety of relatively low cost imaging sensor technologies. The costs of frame-based digital optical sensors have dropped dramatically in recent years thanks to the widespread adoption of digital camera technologies by consumers. However, the relatively limited array size of commercially available digital optical sensors (e.g., 8-24 million pixels) when compared to large format digital optical sensors means they monitor less ground area per unit time at a given resolution, necessitating the deployment of a greater number of sensors to maintain a given temporal resolution. Deployment of un-cooled thermo-optical sensors has also been demonstrated on both LA and UAS platforms. These thermal sensors may enable detection of people and/or vehicles at night. LA and UAS platforms (such as those shown in Figures 1) can easily be equipped with a broad range of sensors to meet different mission requirements.

Figure 1. NEOS FD "Mosquito" light aircraft (left) and remotely piloted UAS imaging platform owned and operated by San Diego State University (right).

Multitemporal Image Co-registration

Two critical preprocessing requirements for image-based change detection are geometric and radiometric registration between multitemporal image pairs. Geometric registration involves the spatial alignment of multitemporal images, so that the location of ground features is consistent between the images. Without precise geometric registration, change artifacts can be introduced into change detection products (Townshend et al., 1992; Dai and Khorram, 1998; Stow, 1999; Verbyla and Boles, 2000; Carvalho et al., 2001; Stow and Chen, 2002). Using the techniques described in Coulter et al. (2003) and Stow et al. (2003), we have consistently achieve spatial co-registration within 2 pixels between multitemporal image sets. For imagery with a spatial resolution of 3-inches (0.08 m), images may be expected to co-register with an accuracy of 6-inches (0.15 m). Even with misregistration on the order of four pixels (1 ft or 0.3 m), we expect to be able to detect changes associated with people/vehicles and their shadows.

Radiometric normalization of multitemporal image products is also an important step prior to change detection analysis. The goal of relative radiometric normalization is to align digital number (DN) values between multitemporal imagery, so that changes in DN value are associated with actual changes in land cover condition. Many methods for relative radiometric normalization of multidate imagery have been proposed and evaluated (Yuan and Elvidge, 1996; Yang and Lo, 2000; Hall et al., 1991). Radiometric normalization may not be necessary when images are collected frequently (e.g., every 15-30 minutes) using the same sensor and exposure/aperture/ISO settings. However, when radiometric normalization is required, automated methods such as histogram matching (based on image mean and standard deviation values) may be employed (Yuan and Elvidge, 1996).

Change Detection Algorithm Introduction

Detecting people and vehicles using traditional image classification techniques is complicated by the fact that the spectral signatures of people and vehicles can vary substantially depending upon the color of the clothing/vehicle and the background features within the image. Shadows cast by people and vehicles are one common denominator that can be expected in most image scenes. However, shadows are also cast by vegetation, rocks, and the terrain itself. It is possible to separate people and vehicle shadows from other shadows not of interest, but this can be a very difficult task to automate as it requires classification/identification of features such as tall vegetation and rock, and buffering around those features to mask out their shadows that are not of interest.

For the detection of moving objects in still, frame imagery collected with high temporal frequency (e.g., repeat-pass every 15 minutes), a novel method is proposed which exploits the high temporal resolution of imagery to aid discrimination of moving objects from other features that are not of interest (i.e., noise). For most image scenes, static features in the scene will exhibit a range of brightness and local texture (variability between adjacent/neighboring pixels) values. The location and magnitude of these brightness and texture variations depend upon the time of day, as sun angles and associated feature shadows/illumination will vary. In addition, wind may cause features such as bushes and trees to physically move. The challenge then is to determine what brightness values and variations in brightness values are expected for any given location (i.e., pixel) within a scene at a particular time of day, and then look for anything that varies from what is expected.

The image-based wide area surveillance system described here utilizes repeat-pass imagery acquired with high frequency from the same camera stations, and therefore a time-series of imagery is available from each imaging station that may be used to determine normal/expected brightness values within image scenes. Scene brightness and texture patterns will change over time as illumination and associated shadow patterns vary throughout the day. Therefore, in order to determine what conditions are normal for a particular time of day (e.g., 12:15 PM), images acquired in the recent past around that same time of day should be utilized. Further, use of imagery from the recent past controls for seasonal illumination and scene changes (e.g., phenology, erosion, etc.).

One methodology that may be implemented is to utilize three images acquired at approximately the same time of day as the subject image (the new image that potentially exhibits changes of interest) for each of the previous seven days. This would yield 21 images that may be utilized to characterize expected brightness and texture patterns at approximately 12:15 PM at this time of year. The three images incorporated from each day would be determined by selecting those that were closest in time to the subject image (e.g., 12:00, 12:15, and 12:30). Change detection may be accomplished by comparing brightness and texture values for pixels in the subject image with those of the time series to determine if a pixels characteristics are outside of the expected range.

To determine what the expected range of brightness and image texture is for any single area corresponding to individual image pixels, the mean and standard deviation of corresponding pixels from the time series are calculated (the assumption is that the temporal data per pixel is normally distributed). This is performed for image brightness values and for image texture values (e.g., 3x3 standard deviation). Brightness and texture values from a newly collected image may then be compared to the time series to determine for each pixel if the new image values are outside of the expected range for that pixel. If the new image's values are outside of the expected range, then a detection occurs. This novel approach for persistent wide area surveillance allows one aircraft to fly flight lines repeatedly and monitor large areas for any objects of interest (people, vehicles, animals, etc.) moving through an area.

PEOPLE AND VEHICLE DETECTION TESTING

To test the above described change detection algorithm for detecting people and vehicles moving through border regions, SDSU worked with NEOS, Ltd to collect high spatial and high temporal resolution imagery for three border sites in San Diego County, CA, USA. Due to limited funding and the remote locations of the border sites, we were not able to collect imagery every day for a week at the same time of day. Instead, we collected several sets of repeat pass imagery over short time periods on a single day to simulate imagery collected over several days.

Study Area and Data

An area near Jacumba, CA was selected to test people and vehicle detection using high spatial and temporal resolution airborne imagery. SDSU personnel worked with Border Patrol agents from the Boulevard Station to locate three sites within the Jacumba area that were representative of border landscapes for the southern United States. These sites are characterized as desert (site 1), grassland (site 2), and chaparral scrub vegetation (site 3). The extent of each site corresponded to the image footprint expected using a Canon EOS 5D Mark II camera system with full resolution and pixels with a ground resolution element of 3-inches (0.08 m). Figure 2 illustrates the diversity of land cover types within each study site.

Imagery was collected on September 29, 2011 using a Flight Design CTSW, 2006 model light aircraft. The 21 MP Canon EOS 5D Mark II camera system was equipped with a 50 mm lens and setup to collect full resolution (5616 x 3744 pixels) RAW format images. RAW format color (RGB) images recorded on the Bayer array were later converted to 3-band TIFF image files. A Track'Air EZtrack navigation and camera triggering system was used to accurately navigate pre-planned flight lines and to automatically trigger the camera at the exact same predetermined camera stations (same horizontal and vertical image station each time, within 20 m or so). Several passes were made down the individual flight lines, collecting repeat-pass imagery approximately every 4-5 minutes. For site 1, nine passes were made over a 40 minute period (9:00-9:40 AM). For sites 2 and 3, thirteen passes were completed over a 55 minute period (10:15-11:10 AM). For site 1, the aircraft flew a race-track pattern and collected imagery with the west/southwest heading each time. Sites 2 and 3 were adjacent to each other, and site 2 was imaged with an east/northeast heading and site 3 was imaged with a west/southwest heading as part of the same race-track pattern.

During the image collections, SDSU and Border Patrol personnel and vehicles moved regularly so as not to be in the same locations on successive imaging passes. For most instances, people moved between each imaging pass. Participants were instructed to move vehicles every ten minutes. However, given the high frequency of imaging passes vehicles were in the same positions for 2-3 imaging passes in several instances.

Change Detection Processing

To simplify processing of the color aerial images, only the red waveband was utilized since it provides good discrimination between scene features such as vegetation, shadow, and soil background (Witztum and Stow, 2004). First, red-waveband images for each individual site were spatially co-registered on a frame-by-by frame basis using the methods described above. Since our automated co-registration approach was still under development, this was accomplished by manually selecting 9-13 matching points between images and co-registering all images to the same reference image. Image warping was accomplished using second-order polynomials and bilinear interpolation. No georeferencing or terrain correction was performed.

Following spatial co-registration, the images for each individual site were radiometrically normalized using a mean-standard deviation normalization technique (Yuan and Elvidge, 1996). To do this, the common area between images in the time series to be utilized for change detection was determined, and mean and standard deviation statistics were extracted from the common area for each individual image and for all images combined. Then, pixel digital number (DN) values from each individual image were adjusted so that the mean and standard deviation of the resulting images matched the overall mean and standard deviation of all images combined (i.e., reference values). This was accomplished using Equation 1. This approach normalized all images radiometrically and accounted for minor variations in illumination, as well as differences in image brightness resulting from varying aperture settings. The camera was set for shutter priority, and aperture subsequently varied between photos due to slight aircraft rotation and resulting variations in scene extent.

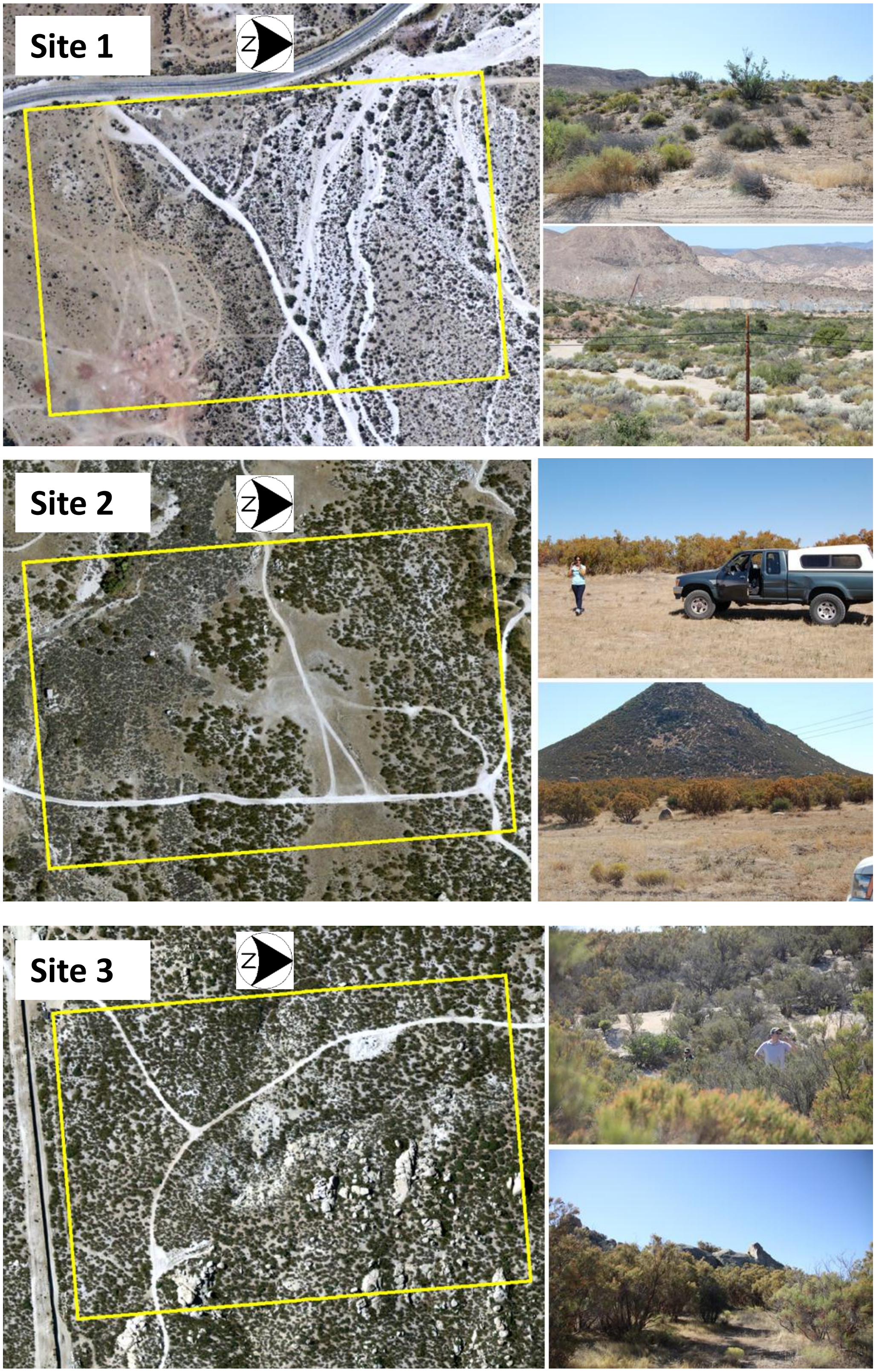

Figure 2. Desert (Site 1), grassland (Site 2), and chaparral (Site 3) study sites near Jacumba, CA. Yellow rectangles indicate planned extent of image area per site, approximately 400 m by 300 m each.

$$(((DN_{sub} - \bar{x}_{sub}) / \sigma_{sub}) * \sigma_{ref}) + \bar{x}_{ref} \quad [1]$$

DN_{sub}	= Digital number value of the subject image to be normalized
$\bar{x}_{sub}$	= Mean of the subject image
σ_{sub}	= Standard deviation of the subject image
σ_{ref}	= Reference Standard deviation
$\bar{x}_{ref}$	= Reference Mean

To detect moving objects at each of the three sites, the below steps were performed with the radiometrically normalized images. SUBJECT IMAGE refers to the image that will be compared against other images in the time series in order to detect changes associated with moving objects. TIME SERIES IMAGES refers to the full sequence of images acquired for each study site from the same camera station. LOCAL IMAGE TEXTURE is calculated as the standard deviation of pixels within a 3x3 window centered on each pixel. A texture image is the image created by calculating LOCAL IMAGE TEXTURE values for each pixel.

1) Compute the mean brightness and standard deviation of brightness between corresponding pixels within the TIME SERIES IMAGES. This provides an indication of the expected range in image brightness on a per pixel-basis. Mean and standard deviation values are calculated based on temporal information (mean over time, and standard deviation over time), on a pixel-by-pixel basis.
2) Compute LOCAL IMAGE TEXTURE for each pixel within the time series and the subject image.
3) Compute the mean LOCAL IMAGE TEXTURE and standard deviation of LOCAL IMAGE TEXTURE (per pixel) between corresponding pixels within the TIME SERIES IMAGES. This provides an indication of the expected range in LOCAL IMAGE TEXTURE. Mean and standard deviation values are calculated based on temporal information (mean over time, and standard deviation over time), on a pixel-by-pixel basis.
4) Identify SUBJECT IMAGE pixels that are brighter than expected. This is accomplished by identifying and setting a threshold value for standard deviations above mean brightness of the TIME SERIES IMAGES. Above this values, the SUBJECT IMAGE pixel is found to be outside of the expected range and is detected as a potential change.
5) Identify SUBJECT IMAGE pixels that are darker than expected. This is accomplished by identifying and setting a threshold value for standard deviations below mean brightness of the TIME SERIES IMAGES. Below this values, the SUBJECT IMAGE pixel is found to be outside of the expected range and is detected as a potential change.
6) Identify SUBJECT IMAGE pixels whose LOCAL IMAGE TEXTURE is greater than expected. This is accomplished by identifying and setting a threshold value for standard deviations above mean LOCAL IMAGE TEXTURE of the TIME SERIES IMAGES. Above this values, the SUBJECT IMAGE pixel is found to be outside of the expected range and is detected as a potential change.
7) To account for any misregistration (misalignment) of images, the expected range of image brightness or LOCAL IMAGE TEXTURE is blurred out by some number of pixels (e.g., 2) in every direction (around each pixel of interest). This is accomplished by calculating the maximum value (in the case of texture or increased SUBJECT IMAGE brightness) or minimum value (in the case of decreased SUBJECT IMAGE brightness) using moving windows (e.g., 5x5).
8) The three change detection products described above (where SUBJECT IMAGE values are outside of the expected range of minimum brightness, maximum brightness, or maximum texture), are merged on a per-pixel basis, so detection for any individual pixel in any of these products is considered a detection result, and no detection occurs when none of the three products indicate a detection.
9) After the three image-based detection results have been merged into one product, portions of the image with isolated detections (e.g., 1,2,3, etc. pixels by themselves) are removed from the detection, so that only larger features of interest remain. This is accomplished using local majority filter windows (e.g., with 3x3 window).

The approach listed above identified image pixels who's characteristics are outside of the expected range. A few adjustable controls were utilized, including: 1) three thresholds of standard deviations around the mean above/below which SUBJECT IMAGE brightness or texture values must fall in order to indicate a detection of a moving object, 2) the distance at which misregistration is accounted for by raising or lowering (on a local basis) threshold values so that misregistration is not causing false detection, and 3) the size of the focal majority window that is utilized to identify and remove isolated false detections. Using this approach, threshold settings were unique per pixel, allowing varying sensitivity depending upon the scene background at individual pixels. Further, only three actual standard deviation values were specified to establish these varying/pixel-specific thresholds, so adjusting and fine tuning thresholds to change the sensitivity required for detection was simple.

The automated temporal thresholding (ATT) approach to change detection described above was applied to nineteen total images, including five from site 1, seven from site 2, and seven from site 3. The images utilized were from the middle part of the imaging sequence, so that any variations in shadow, etc. would be accounted for by the wider temporal range of the full time series.

RESULTS AND DISCUSSION

Examples of people and vehicle changes detected using the 3-inch spatial resolution imagery and the automated temporal thresholding approach are provided in Figures 3 and 4. Table 1 lists the detection accuracy per site and for all combined sites. A person or vehicle was considered to be detected if one or more pixels indicated a change. The detection accuracy was 98% for people and 100% for vehicles, when the people and vehicles changed positions between each imaging pass. Given our limited number of image frames in the time series, people and vehicles that didn't move frequently enough between imaging passes became part of the expected variation (i.e., part of the image background). For sites 2 and 3, many vehicles and three people did not move enough to be detected as change. The only missed detection (site 1) was associated with a person who stood next to and in the shadow of a vehicle that didn't move between two imaging passes, and the person was not detected due to the high variability at that location (bright soil in some images and dark shadow in others). If this person was in an area with natural background, the detection rate for people may have been 100%. There were only four occurrences of falsely detected features (12 pixels total), which occurred only in one of the nineteen scenes evaluated. These falsely detected features were associated with shadows from power poles or power lines, which changed position as the sun moved across the sky.

For this study, all image co-registration, radiometric normalization, change detection processing, and threshold selection was accomplished using human interaction. However, the steps are straightforward to implement using automated routines and our team is working toward this goal. We have implemented and are refining automated image co-registration routines. Radiometric normalization simply requires that common areas be identified and global statistics calculated. The change detection routine also relies on simple image statistics. The threshold values and window sizes utilized for change detection will be established through testing and through interactive modification during operations. Further, using two-way communications, all settings (thresholds, window size correcting for residual mis-registration, and post-classification majority filtering) could be adjusted during flight when needed.

In this study, sites 2 and 3 utilized the "racetrack" approach to image collection. All change detection settings (thresholds and window sizes) were the same for these two sites demonstrating that the fixed settings worked for two different sites collected at the same time of day. The threshold settings for site 1 varied from those of sites 2 and 3, possibly due to different times of day (we're investigating why different settings were optimal). Threshold settings for site 1 in values of standard deviations from the mean were 2.1, 2.3, and 2.1 for texture increase, red waveband decrease, and red waveband increase, respectively. Threshold settings for sites 2 and 3 in values of standard deviations from the mean were 2.8, 2.5, and 2.6 for texture increase, red waveband decrease, and red waveband increase, respectively

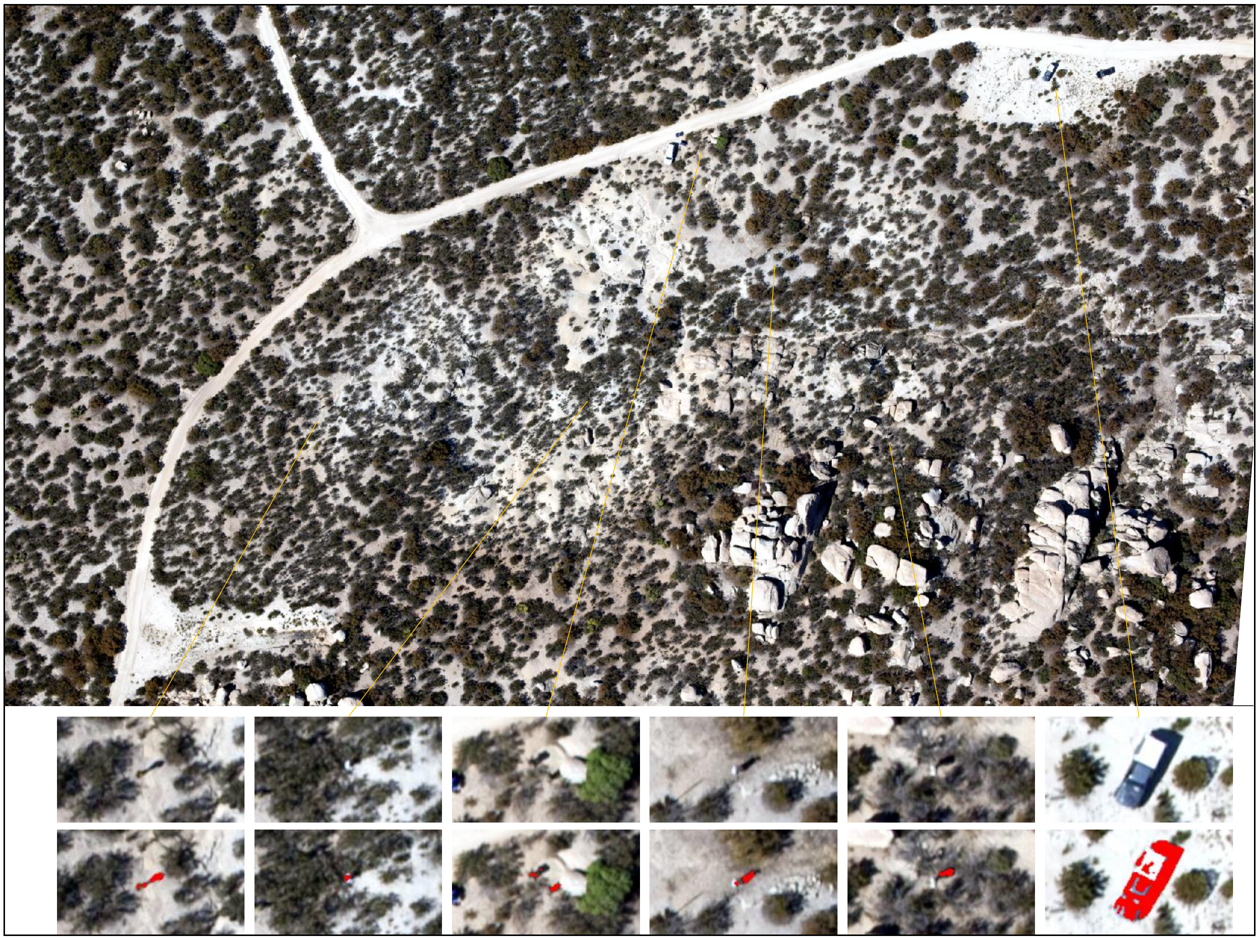

Figure 3. Image-based detection of people and vehicles moving within the U.S./Mexico border region. SDSU and Border Patrol personnel are detected as they move through a redshank chaparral area (site 3) near Jacumba, CA. Red indicates detection of movement, as people or vehicles were not at the current location during the previous imaging passes. Vehicles not detected did not move between imaging passes. All people and moving vehicles were detected, with no false detection (commission error).

Figure 4. Image-based detection of people and vehicles moving within the U.S./Mexico border region. SDSU and Border Patrol personnel are detected as they move through a desert area (site 1) near Jacumba, CA. Red indicates detection of movement, as people or vehicles were not at the current location during the previous imaging passes. All people and moving vehicles were detected, with no false detection (commission error).

Table 1. People and vehicle detection results for nineteen images evaluated. Counts are for the total number of objects detected considering all image scenes evaluated.

	People	**Vehicles**	**Commission Error**
Desert	94% (15/16)	100% (9/9)	4 occurrences (power pole/line shadow)*
Grassland	100% (15/15)	100% (1/1)	
Chaparral/Scrub	100% (33/33)	100% (1/1)	
Overall	98% (63/64)	100% (11/11)	

* Can be filtered out if regularly occurring

CONCLUSIONS

High spatial resolution airborne imagery may be used to detect and monitor people and vehicles moving through border regions. When imagery is acquired with high temporal frequency and exploited for detection purposes, every image pixel essentially acts as a sensor that may be set off when objects change position in the scene. Near real-time detection using image-based monitoring will allow agents to visually verify detected change features on their computer screens as they are detected, and to instantly identify on a map the locations of these features of interest.

The patent pending approach to persistent wide area surveillance described above enables individual or multiple low-cost systems to monitor large geographic areas. The goal is to detect and intermittently track previously undetected objects, rather than provide continuous surveillance as many video system do. However, if multiple systems are in the air, one could switch from wide area monitoring to continuous tracking when objects of interest are detected. Factors influencing the extent of area monitored include: the size and number of imaging arrays on each platform, the spatial resolution of the imagery, aircraft velocity, and the number of systems utilized. It is envisioned that airborne monitoring would be utilized for selected areas of interest, and these areas will change depending upon activity and overall strategy.

Results from our test in three different environments indicate that the approach detects nearly 100% of people and vehicles, with virtually no false detections. We are currently seeking funding to develop and test a fully automated detection system. In addition, we hope to test the utility of high spatial resolution (e.g., 2 m) thermal imagery for night time detection of people and vehicles.

LA and UAS systems offer low cost, scientific imaging capability for persistent wide area surveillance. Implementation of affordable, airborne imaging and near real-time change detection capability will provide valuable tools and information that support the mission of the Border Patrol and aid daily operations. Derived information products will further augment existing tools and sensor information streams.

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REFERENCES

Carvalho, L., L. Fonseca, F. Murtagh, and J. Clevers. 2001 . Digital change detection with the aid of multiresolution wavelet analysis. *International Journal of Remote Sensing*, 22 (18): 3871-3876.

Coulter, L., D. Stow, and S. Baer. 2003. A frame center matching approach to registration of high resolution airborne frame imagery. *IEEE Transactions on Geoscience and Remote Sensing*, 41(11): 2436-2444.

Coulter, L. and D. Stow. 2005. Detailed change detection using high spatial resolution frame center matched aerial photography. In: *Proceedings of the 20th Biennial Workshop on Aerial Photography, Videography, and High Resolution Digital Imagery for Resource Assessment*, October 4-6, 2005, Weslaco, Texas.

Coulter, L. and D. Stow. 2008. Assessment of the spatial co-registration of multitemporal imagery from large format digital cameras in the context of detailed change detection. *Sensors*, 8: 2161-2173.

Coulter, L. and D. Stow. 2009. Monitoring habitat preserves in southern California using high spatial resolution multispectral imagery. *Environmental Monitoring and Assessment*, 152: 343-356.

Coulter, L., C. Lippitt, D. Stow, and R. McCreight. 2011. Near real-time change detection for border monitoring. *Proceedings from the ASPRS annual conference*, Milwaukee, WI, May 1-5, 2011.

Dai, X. and S. Khorram. 1998. The effects of image misregistration on the accuracy of remotely sensed change detection. *IEEE Transactions on Geoscience and Remote Sensing*, 36(5): 1566-1577.

Davies, A.G., S. Chien, V. Baker, T. Doggett, J. Dohm, R. Greeley, F. Ip, R. Castano, B. Cichy, G. Rabideau, D. Tran, and R. Sherwood. 2006. Monitoring active volcanism with the autonomous sciencecraft experiment on EO-1. *Remote Sensing of Environment*, 101: 427-446.

Hall, F., D. Strebel, J. Nickeson, S. Goetz. 1991. Radiometric rectification: Toward a common radiometric response among multidate, multisensor images. *Remote Sensing of Environment*, 35, 11-27.

Herwitz, S.R., L.F. Johnson, S.E. Dunagan, J.A. Brass, and G. Witt. 2003. Orchestrating a near-real-time imaging mission in the National Airspace using a solar-powered UAV. In *2nd AIAA UAV*, San Diego, CA.

Ip, F., J.M. Dohm, V.R. Baker, T. Doggett, A.G. Davies, R. Castano, S. Chien, B. Cichy, R. Greeley, R. Sherwood, D. Tran and G. Rabideau. 2006. Flood detection and monitoring with the autonomous sciencecraft experiment onboard EO-1. *Remote Sensing of Environment*, 101: 463-481.

Joyce, K.E., S.E. Belliss, S.V. Samsonov, S.J. McNeill & P.J. Glassey. 2009. A review of the status of satellite remote sensing and image processing techniques for mapping natural hazards and disasters. *Progress in Physical Geography*, 33: 183-207.

Laliberte, A.S., J.E. Herrick, A. Rango, C. Winters. 2010. Acquistion, orthorectification, and object-based classification of unmanned aerial vehicle (UAV) imagery for rangeland monitoring. *Photogrammetric Engineering & Remote Sensing*, 76(6): 661-672.

Li, L. and M. K. H. Leung. 2002. Integrating intensity and texture differences for robust change detection. *IEEE Transactions on Image Processing*. 11(2): 105-112.

Office of Border Patrol. 2004. *National Border Patrol strategy*. Office of Border Patrol, U.S. Customs and Border Protection, document prepared by the Office of Border Patrol and the Office of Policy and Planning, September, 2004.

Stow, D. 1999. Reducing the effects of misregistration on pixel-level change detection. *International Journal of Remote Sensing*, 20(12): 2477-2483.

Stow, D. and D. Chen. 2002. Sensitivity of multitemporal NOAA AVHRR data of an urbanizing region to land-use/land-cover changes and misregistration. *Remote Sensing Environment*, 80: 297-307.

Stow, D., L. Coulter, and S. Baer. 2003. A frame centre matching approach to registration for change detection with fine spatial resolution multi-temporal imagery. *International Journal of Remote Sensing*, 24: 3873-3879.

Stow, D., Y. Hamada, L. Coulter, and Z. Anguelova. 2008. Monitoring shrubland habitat changes through object-based change identification with airborne multi-spectral imagery. *Remote Sensing of Environment,* 112: 1051-1061.

Stow, D., L. Coulter, and C. Benkelman. 2009. Airborne Digital Multispectral Imaging. In *The SAGE Handbook of Remote Sensing*, G. Foody, T. Warner, and M. D. Nellis (eds), SAGE Publications, London.

Stryker, T. and B. Jones. 2009. Disaster response and the international charter program, *Photogrammetric Engineering and Remote Sensing*, 75: 1242-1344.

Thomas, C., T. Ranchin, L. Wald, and J. Chanussat. 2008. Synthesis of Multispectral Images to High Spatial Resolution: A Critical Review of Fusion Methods Based on Remote Sensing Physics. *IEEE Transactions on Geoscience and Remote Sensing*, 46(5): 1301-1312.

Townshend, J., C. Justice, C. Gurney, and J. McManus. 1992. The impact of misregistration on change detection. *IEEE Transactions on Geoscience and Remote Sensing*, 30(5): 1054-1060.

Verbyla, D. and S. Boles. 2000. Bias in land cover change estimates due to misregistration. *International Journal of Remote Sensing*, 21(18): 3553-3560.

Villa, P. and G. Lechi. 2007. Normalized difference reflectance: an approach to quantitative change detection. *Proceedings of the 2007 IEEE International Geoscience and Remote Sensing Symposium*, IGARSS 2007, Barcelona, Spain, pp: 2366-2369.

Witztum, E. and D. Stow. 2004. Analysing direct impacts of recreation activity on coastal sage scrub habitat with very high resolution multi-spectral imagery. *International Journal of Remote Sensing*, 25(17): 3477-3496.

Yang, X. and C. Lo. 2000. Relative radiometric normalization performance for change detection from multi-date satellite imagery. *Photogrammetric Engineering and Remote Sensing*, 66(8): 967-980.

Yuan, D. and C. Elvidge. 1996. Comparison of relative radiometric normalization techniques. *ISPRS Journal of Photogrammetry and Remote Sensing*, 51: 117-126.

Zha, Y., J. Gao, and S. Ni. 2003. Use of normalized difference built-up index in automatically mapping urban areas from TM imagery. *International Journal of Remote Sensing*, 24(3): 583-594.