AUTOMATED CO-REGISTRATION OF MULTITEMPORAL AIRBORNE FRAME IMAGES FOR NEAR REAL-TIME CHANGE DETECTION

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ABSTRACT

Advances in aerial platforms, imaging sensors, image processing/computing, geo-positioning systems, and wireless communications make near real-time change detection more practical and cost effective. In Coulter et al. (2003) and Stow et al. (2003), we documented a method for collecting and precisely co-registering multitemporal airborne frame imagery that minimizes terrain and image features distortion differences between images, and enables precise relative alignment using simple techniques. This patent pending method is referred to as frame center matching. Here we describe specific procedures for automating the co-registration of frame center matched images. This type of rapid and automated image co-registration may support real-time or near real-time change detection, where newly acquired and previously acquired frame center matched images are aligned and compared on-board as an aircraft flies. The steps for automation include pairing multitemporal image sets, utilizing airborne Global Positioning System (GPS) and inertial measurement unit (IMU) data for initial alignment of images, automated control point collection, evaluation of control point pairs, image transformation, and assessment of image co-registration quality. This work is developed by the National Center for Border Security and Immigration: A Department of Homeland Security (DHS) Science and Technology (S&T) Center of Excellence. This work is also developed by the Infrastructure Protection and Disaster Management Division of DHS S&T.

KEYWORDS: image registration, automated, change detection, real-time, airborne, sensor orientation.

INTRODUCTION

Advances in microprocessors and communication technology have enabled advances in automated image processing and information 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).

San Diego State University (SDSU) is developing methods for near real-time change detection using frame-based airborne imagery, specialized image collection methods, and automated image processing routines. This capability has several applications including rapid post-disaster (e.g., earthquake) assessment, wildlife tracking, and persistent surveillance for people and vehicle detection across broad areas such as battlefields or border regions.

Detection of detailed land cover or feature changes using multitemporal imagery requires precise geometric co-registration between image sets. However, precise co-registration of imagery acquired from airborne platforms traditionally takes substantial analyst interaction and supporting data such as high quality terrain models and surveyed ground control. For many applications, image-based change detection products are needed as quickly as possible and their utility decreases over time. Achieving precise spatial co-registration of high resolution multitemporal imagery in near real-time using automated procedures is not trivial. However, we use specific image collection and processing techniques that minimize terrain related distortion between image sets and enable relatively simple image processing techniques to achieve precise spatial co-registration.

Methods for collecting and spatially co-registering high spatial resolution, 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). Use of such imagery enables the detection of very small changes between multitemporal image sets (Stow et al., 2008; Coulter and Stow, 2009). The objective of this paper is to describe procedures and considerations for the automated co-registration of airborne image frames for near real-time change detection.

BACKGROUND

Image registration involves geometrically or spatially aligning two or more images so that they may be compared or utilized together. Such images may have been collected from different positions (or viewpoints), different sensors (i.e., multimodal), or collected at different times (i.e., multitemporal). Image registration has a wide range of application fields, including medical imaging (e.g., comparing X-ray images over time to see if a tumor has grown), computer vision (e.g., analyzing video imagery for object recognition or industrial inspection), and remote sensing (Brown 1992; Zitová and Flusser, 2003; Wyawahare et al., 2009). In the context of remote sensing, image registration is often used to prepare airborne or satellite imagery for change detection, image classification, and image fusion.

Image registration is utilized to transform a subject image so that it is geometrically aligned with a reference image and generally involves three primary steps: 1) feature matching, 2) transform model estimation, and 3) image resampling and transformation (Zitová and Flusser, 2003; Wyawahare et al., 2009). Feature matching identifies corresponding image coordinate sets between the images that may be utilized to estimate the transformation model. Feature matching may be accomplished using feature-based or area-based approaches. Transform model estimation is the process of estimating and possibly fine tuning the transformation model in order to achieve accurate image registration. The derived transformation model is the best estimate given available information, and each observed control point is likely to have some level of residual error compared to the model. Once a final transformation model is attained, the subject image may be transformed and resampled (converting subject image pixel values from the subject image grid to the reference image grid).

Feature-based matching involves feature detection with subsequent matching of detected features. Feature detection is the process of identifying specific image features and characterizing these features using a range of possible descriptors. Feature selection may be based upon the characteristics of regions, edges, contours, line intersections, and corners (Bentoutou, et al., 2005). Feature matching utilizes a variety of information to compare image feature characteristics between image sets to identify feature pairs that meet specified matching criteria. Image coordinates from successfully matched feature pairs may be utilized to co-register the images.

The spatially invariant feature transform (SIFT) proposed by Lowe (2004) is a well known descriptor routine that has been widely used. SIFT generates a large number of feature points per image, and uses 128 unique feature descriptors in order to achieve robust matching of individual features between the subject and reference image. Since it was first proposed in 2004, variations on the SIFT routine have been published (Song et al., 2010; Sedaghat, et al., 2011). Other feature-based descriptors include Gaussian derivatives, moment invariants, and shape context (Floravk et al., 1994; Mindru et al., 2004, Belongie et al., 2002). Matching features may be accomplished based on either feature descriptors or spatial relationships (Fischler and Bolles, 1981; Stewart, 1999). Feature based methods robustly handle images with intensity and geometric distortion differences, but they may yield too few or unevenly distributed matched points (Liu et al., 2006).

Area-based matching involves the comparison of local windows of image digital number (DN) values. These values could be based upon original image intensity or transformed image products. Area-based matching skips the feature detection step and directly searches for matching characteristics between pixel values of the subject and reference images. Area-based matching methods include: cross-correlation, least squares, mutual information, Fourier, maximum likelihood, statistical divergence, and implicit similarity matching (Wyawahare et al., 2009; Sedaghat et al., 2011; Zitová and Flusser, 2003). Area-based methods generally require initial, coarse alignment between images (Lui et al., 2006). Area-based methods yield sub-pixel matching accuracy, but are less effective than feature-based approaches for images with repeating textures, illumination differences, or image distortions (Sedaghat et al., 2011). Further, area-based methods also may not be appropriate for images collected from different locations and having wide baselines (Wu et al., 2011).

Transformation model estimation includes selecting a transformation model based upon the method of image acquisition, the assumed geometric deformation, and the required accuracy of the registration (Zitová and Flusser, 2003). Global transformation models (single model applied across entire images) include affine, projective, polynomial-based approaches, each of which is applicable for specific situations (Zitová and Flusser, 2003). Bivariate polynomial models enable simple rotation, translation, and scaling. Affine models are appropriate for registration of image scenes acquired from different viewing perspectives, if a perfect (pin hole) camera is used, the camera is far from the scene imaged, and the surface imaged is flat. When the camera is close to the scene, then projective models are appropriate in order to handle scale changes from one edge of the scene to the other. For scenes with complex distortions (e.g., terrain relief from aerial sensors), second or third order polynomial models may be more appropriate (Zitová and Flusser, 2003). Local transformation models include piecewise linear and piecewise cubic mapping (Zitová and Flusser, 2003). Local models are appropriate when distortions vary over short distances. Local models generally require a large number of accurate control points in order to generate local transformations.

Transformation of the subject image to match the positioning and inherit the grid of the reference image requires the subject image to be resampled. Resampling is the digital process of estimating new image pixel values from the original image pixel values when the image grid position or size is changed (Parker et al., 1983). Depending upon the interpolation method used, original DN values or modified DN values result. Resampling methods include: nearest neighbor, bilinear interpolation, and bicubic functions (Zitová and Flusser, 2003).

MULTITEMPORAL IMAGE COLLECTION AND CO-REGISTRATION

Multitemporal Image Collection using Matched Frame Centers

The Department of Geography at SDSU developed methods for acquiring and processing imagery so that near pixel-level spatial co-registration between high spatial resolution (0.15 m or 0.5 ft) multitemporal image sets may be attained (Coulter et al., 2003; Stow et al., 2003). This is a remarkable technical achievement considering the fine image spatial resolution and highly variable terrain relief of the study areas used for testing the image registration techniques. With these techniques, very detailed land cover changes may be detected (Coulter and Stow, 2005; Coulter and Stow, 2008; Stow et al., 2008; Coulter and Stow, 2009).

Image acquisition procedures that enable precise spatial co-registration between multitemporal image frames are described in Coulter et al. (2003). The approach referred to as frame center (FC) matching is based upon matching camera stations in terms of horizontal position and altitude between multitemporal image acquisitions (Figure 1).

Matching image stations is most effectively accomplished through the use of Global Positioning System (GPS) technology to aid the pilot in maintaining the desired track and altitude, and automatically trigger image capture at the same camera station previously visited during the first multitemporal pass. Four specific tools required for operational frame center matching using GPS data are:

1. GPS for logging and digitally archiving flight line and frame center coordinates for each image acquisition.
2. Flight planning software integrated with digital coordinates of flight line and frame coordinates from previous image dates.
3. In-flight, heads-up display enabling pilot to maintain flight line course and altitude (based on GPS coordinates).
4. Automatic triggering of image frames (based on digitally archived coordinates and in-flight GPS).

When image frames are captured from exactly the same camera station between multitemporal acquisitions, there is no parallax between the images, and they may be expected to exhibit the same terrain related geometric distortions (assuming that differences in camera attitude are negligible). Further, the relative spatial position of features within the images is consistent between image sets (i.e., no local distortion differences) and the individual image frames may be precisely co-registered using simple warping functions.

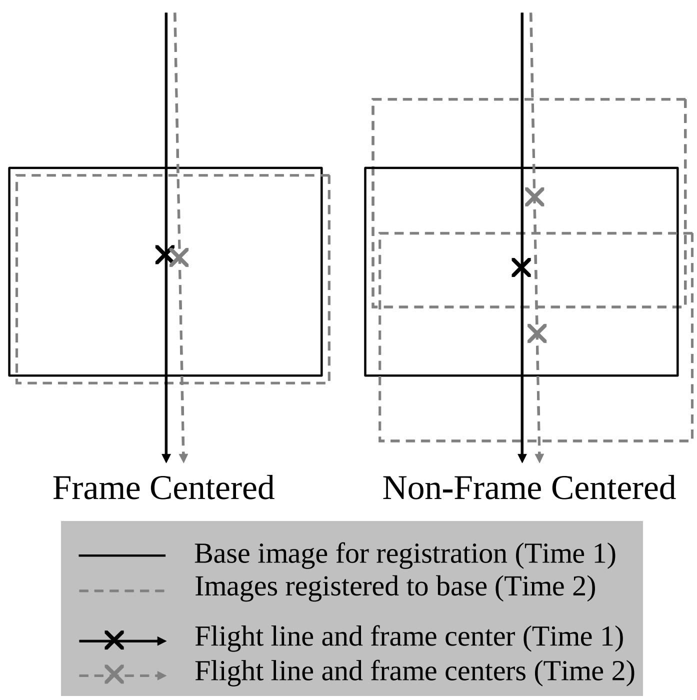


Figure 1. Position of frame center and non-frame center matched images relative to a registration base image. Source: Coulter et al., 2003.

Geometric Co-registration using Frame Center Matched Images

Geometric co-registration of multitemporal images is critical for image-based change detection (Toutin, 2004). 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 describe in Coulter et al. (2003) and Stow et al. (2003), we have consistently achieved 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 with 3-inch spatial resolution imagery), detailed changes may be detected.

Image acquisition using the FC matching approach described above yields multitemporal image frame pairs with similar ground coverage, which exhibit nearly identical spatial distortions since they are captured from the same viewing point. Achieving precise multitemporal spatial co-registration requires that the FC matched image sets be spatially co-registered on a frame-by-frame basis (Coulter et al., 2003; Coulter and Stow, 2008). General procedures for processing and precisely co-registering image pairs are described below and illustrated in Figure 2. Following these image co-registration procedures, detection of feature changes between image frames may be accomplished.

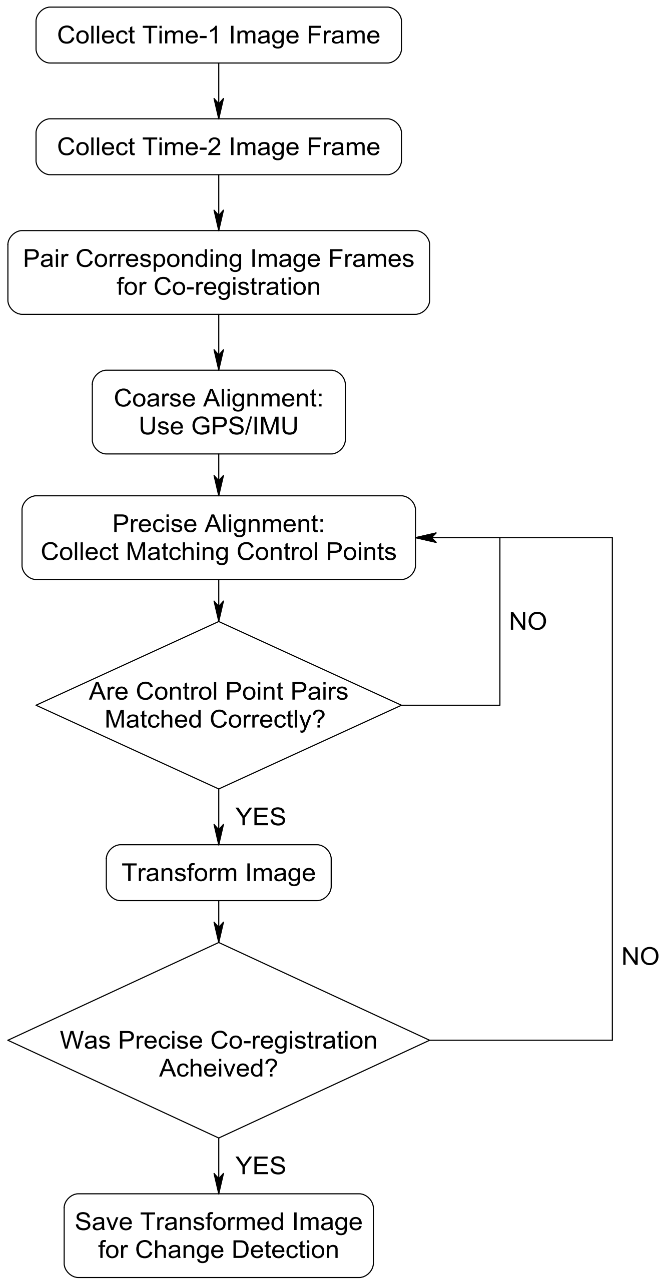


Figure 2. Image co-registration processing flow.

Image Pairing

Near real-time change detection may be accomplished by collecting repeat-pass image frames at one or more camera stations. The first step in utilizing multitemporal images for change detection is to determine which images represent FC matched pairs. This may be accomplished using GPS data collected for each image frame. The general accuracy of GPS non-differentially corrected positions is +/- 10 m. Therefore, matched photo stations between multitemporal imaging passes may be expected to be within +/- 20 m (plus a few extra meters for timing errors associated with GPS-based camera triggering). Positions of individual image stations are likely to be hundreds of meters apart, so determining which images belong to which camera station is trivial. It is also worth noting that services like the Wide Area Augmentation System (WAAS) may also be used to differentially correct the GPS data and further reduce errors.

Coarse Image Alignment

The image registration approach to be utilized relies on area-based matching (as described below). Area-based matching requires that images be coarsely aligned so that small search distances for matching pixel windows may be used. This reduces processing loads and decreases the likelihood of finding false point matches. Coarse image alignment will be accomplished through direct georeferencing using GPS and inertial measurement unit (IMU) data collected for each image frame (Stow et al., 2009). GPS data provides the horizontal and vertical position of the aircraft (X, Y, and Z), while IMU data provides rotation angles of the aircraft (Omega, Phi, and Kappa). Given the information from the GPS and IMU, real-world coordinates may be assigned to each pixel and provide the basis for coarse image alignment (e.g., both images positioned within 10 m of real-world positions).

Precise Image Alignment Using Area-Based Matching

Precise image alignment will be accomplished with control points collected using area-based matching techniques for image registration. Area-based matching techniques are utilized because they provide sub-pixel matching, a high number of evenly distributed control points, they do not rely on presence of discrete features in the image, and because no significant geometric distortions are expected between the FC matched images. Further, area-based approaches are appropriate because image registration is performed with images collected using the same sensor under similar illumination conditions (e.g., 15-30 minutes apart).

Area-based matching may utilize normalized cross correlation (NCC) algorithms or mutual information (MI) algorithms (Lui et al., 2006; Zitová and Flusser, 2003; Chen et al., 2003; Suri and Reinartz, 2010). We have tested both approaches and each is highly successful at generating matched points between FC matched images. The NCC approach utilizes image digital number values, while the MI approach uses digital number value distributions. Reference image control point (CP) locations and corresponding initial locations for matched CPs in the subject image can either be selected based on high entropy values, a regular grid pattern (for well distributed points), or a combination of both in order to yield high quality and well distributed control points. Window sizes and search distances utilized when finding corresponding control points between reference and subject images may be adjusted depending upon the image characteristics and initial (coarse) alignment between images, respectively. In addition, the number of points sought for matching and their systematic distribution across the reference image may be specified as part of the control point collection process. Reduced resolution images may also be used with area-based matching to change the scale of analysis while maintaining relatively small window sizes (Lee, 2010).

Removing False Point Matches

After initial control point pairs (CPP) have been collected, it is necessary to identify and remove any false matches as maintaining these points will adversely affect image registration. This will be accomplished using the random sample consensus (RANSAC) method for iteratively estimating model parameters. This method was first proposed by Fischler and Bolles (1981), and has been widely utilized for identifying mismatched control points for image registration (Lee, 2010; Wu et al., 2011). Rather than considering all points to create a transformation model and then looking for points with high relative error, RANSAC samples a small number points, determines a model, then compares other points to the model. If the errors associated with the new points are mostly due to measurement error (small, expected variation) then the points are added to the solution and the model is recalculated. Points whose errors are too large to be measurement errors (and therefore indicate mismatched features) are excluded from the model. RANSAC continues until model consensus is reached for a minimum number of points. If consensus based upon a threshold number of points is not reached, then the majority or plurality of points is taken as the solution or the process terminates in failure.

Image Transformation

The subject image is transformed once a set of correctly matched control points are collected. We have found through experience with high spatial resolution airborne imagery that second-order polynomial transformations are appropriate for co-registering frame center matched airborne image frames. Second-order polynomial transformations can successfully align images with slight view angle differences (associated with aircraft roll and pitch) and minor terrain-related distortion differences that may result when photo station positions are slightly offset (either horizontally or vertically) (Toutin, 2004). During the transformation process, images may be resampled using bilinear interpolation or bi-cubic approaches. Nearest neighbor resampling is not recommended because of the disjointed appearance in the output image and due to spatial offsets as great as one-half pixel. Bilinear interpolation is recommended as it maintains accurate positional quality, with minimum processing overhead and minimum modification of the original pixel values.

Assessment of Co-registration Accuracy

It is necessary to evaluate the quality of the image co-registration in order to have confidence in change detection products generated from multitemporal image sets. One way to accomplish this is to generate a new set of matched points between the reference image and the transformed subject image using a different algorithm or different algorithm parameters. These may be used as independent test points. The root mean square error (RMSE; Equation 1) may then be computed from these independent test points and utilized as a basis for determining acceptable or non-acceptable image co-registration. When registration is acceptable, the transformed image is saved and made available for subsequent change detection analysis processing.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\Delta X_i^{2} + \Delta Y_i^{2}\right)} \qquad [1]$$

Where:

n = the number of test points
i = test point (TP) number
ΔX_i = the X misregistration distance for TP_i
ΔY_i = the Y misregistration distance for TP_i

Status of Development

The utility of the frame center matching approach for achieving precise alignment between multitemporal images has been demonstrated with several camera systems, platforms, land cover types, and image spatial resolutions, consistently achieving co-registration accuracy (RMSE) within approximately 2 pixels (Coulter et al. (2003), Stow et al. (2003), Coulter and Stow (2005), Coulter and Stow (2008), Stow et al. (2008), Coulter and Stow (2009), and Coulter et al. (2011). However, these studies have utilized manual control point collection to align the images. We are currently implementing and refining automated procedures to complete the processing steps outlined in Figure 2. Examples of image pairs registered using automated routines are given in Figure 3 and Figure 4. Figure 3 illustrates two 1 m spatial resolution image frames acquired in 1998 (Time-1) and 2005 (Time-2), and their resulting alignment following automated registration. The accuracy of co-registration (RMSE) is 1.4 pixels (1.4 meters). Figure 4 illustrates two 0.08 m spatial resolution images acquired within minutes of each other in October 2011, and their resulting alignment following automated registration. The accuracy of co-registration (RMSE) between these image frames is 1.3 pixels (0.1 meters). Achieving this level of precise image alignment in near real-time using automated techniques will benefit many applications where rapid change detection is needed.

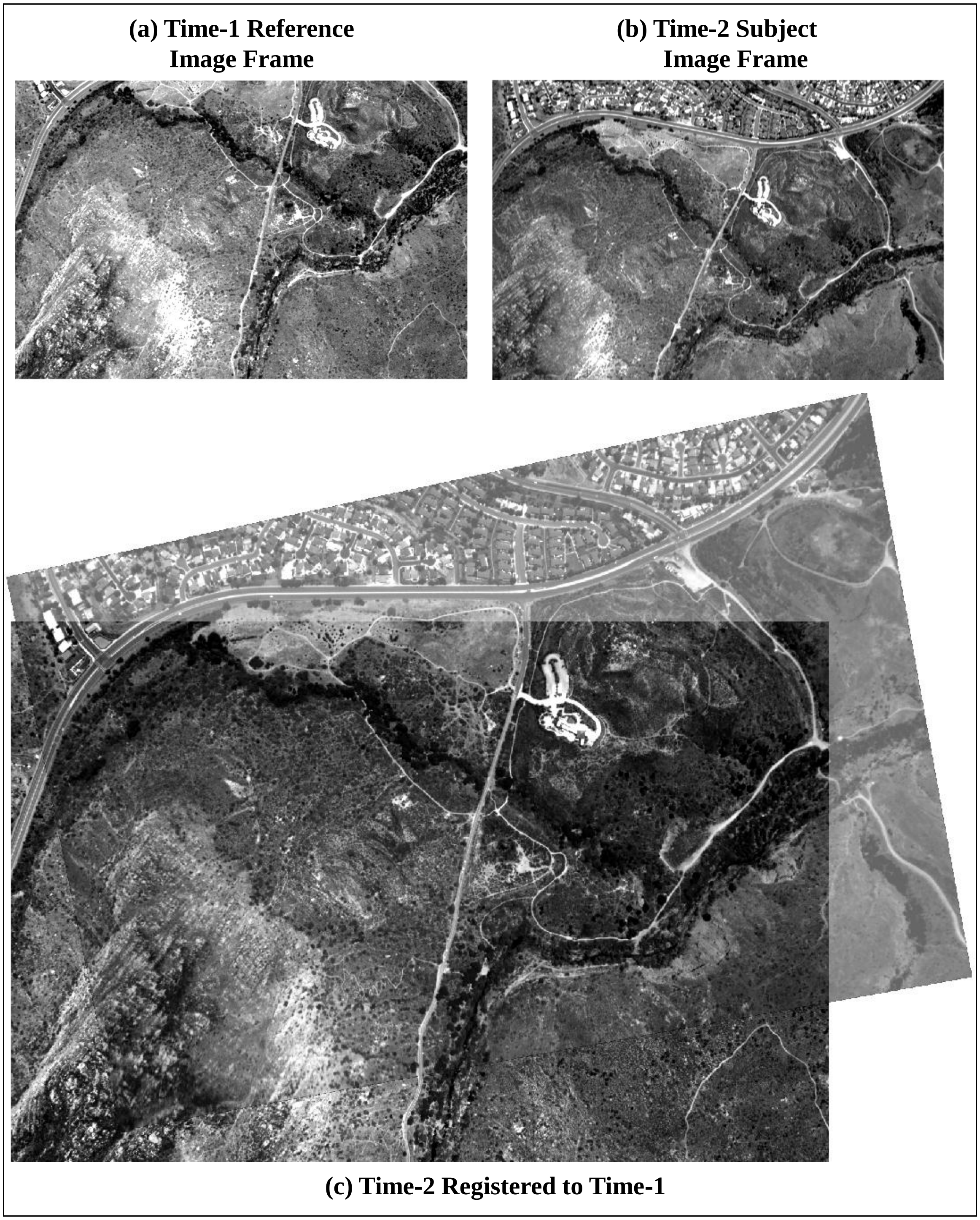
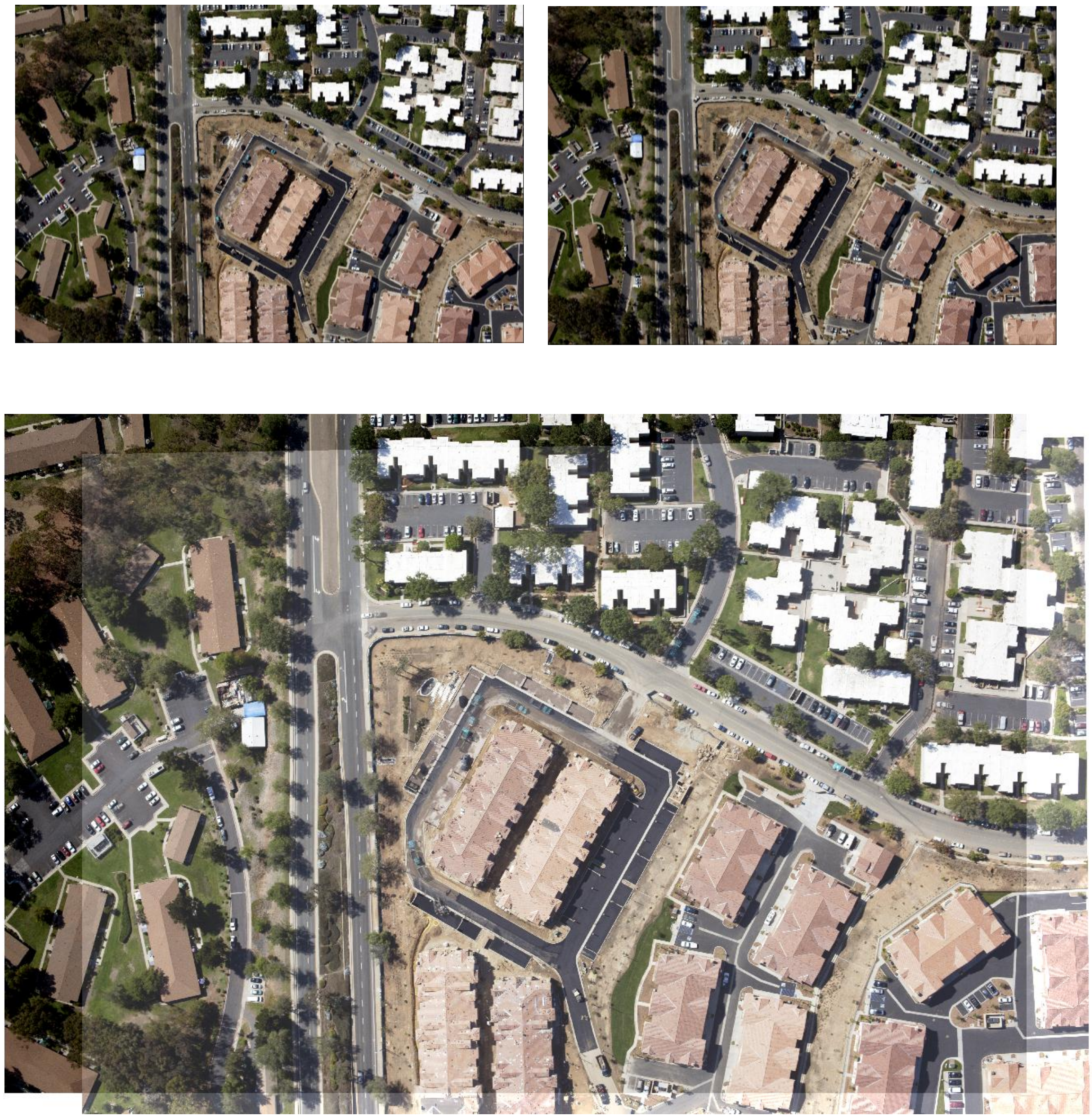


Figure 3. Image co-registration example using frame center matched images processed on a frame-by-frame basis. The 1 m spatial resolution images of a San Diego, CA regional park are precisely aligned. The Time-2 image is displayed with lighter tone.

(a) Time-1 Reference Image Frame

(b) Time-2 Subject Image Frame



(c) Time-2 Registered to Time-1

Figure 4. Image co-registration example using frame center matched images processed on a frame-by-frame basis. The 0.8 m spatial resolution images from a multiple family residential area under construction are precisely aligned. The Time-2 image is displayed with lighter tone.

CONCLUSIONS

Multitemporal image sets utilized for change detection must be precisely co-registered so that real changes are detected and false changes are not introduced. In this paper we have outlined procedures for collecting and co-registering airborne frame images in an automated fashion for near real-time change detection. The approach does not require ground control points for accurate positioning of imagery, terrain correction, nor mosaicking of image frames. Instead, the approach uses special image collection and processing procedures that operate on a frame-by-frame basis to achieve precise spatial co-registration for detailed change detection. This patent pending approach for rapid and automated alignment of multiemporal imagery is supported by several studies and peer reviewed publications by the authors. While specific procedures are listed here, we anticipate that these procedures will be incrementally improved and made more efficient with operational testing and use.

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