Reducing the effects of misregistration on pixel-level change detection

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Abstract. A model that compensates for misregistration effects on change detection results shows promise for reducing artefacts and enhancing land change features at or near the pixel scale and for reducing noise caused by misregistered multi-temporal images. Sparse estimates of misregistration across the scene are combined with calculations of spatial brightness gradients to adjust the magnitude of multi-temporal image differences. The model is tested on a multi-temporal Landsat Thematic Mapper image data set for a rapidly urbanizing landscape in southern California.

1. Introduction

Information on the location, distribution, and amount of land cover change is sought by a wide range of scientists and practitioners including Earth systems scientists, land resource managers and urban planners, and business people. The application of remotely sensed data for assessing land cover change (frequently called 'change detection') is one of the most successful implementations of remote sensing (Singh 1989). However, the success of change detection may be dependent on the precision of relative alignment between images that compose a multi-temporal data set.

Accurate spatial registration is the most critical image processing requirement for reliable assessment of land cover changes that occur at spatial scales that are close to the characteristic dimensions of the ground resolution element of the imagery used to assess changes (i.e. ‘pixel-level’ change). Dai and Khorram (1997) showed that highly accurate change detection based on multi-temporal Landsat Thematic Mapper (TM) images requires that the magnitude of misregistration be less than 0.2 pixel. Townshend et al. (1992) demonstrated that even when the precision of registration for relatively coarse resolution data, such as from the National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR), approaches one-quarter of a pixel, artefacts from image differencing of misregistered spectral vegetation index (SVI) values are likely to be more prevalent than SVI difference values from actual land cover change. A key finding from Townshend et al. (1992) was that the misregistration effects on image differencing were greatest for multi-temporal data sets of regions that were spatially heterogeneous.

One of the few studies to develop compensation approaches for misregistration
effects on image change detection was that of Gong et al. (1992). The authors tested two approaches for minimizing the effects of misregistration: (1) image smoothing, and (2) adaptive grey-level filtering. The image smoothing approach, which is achieved by applying a moving average or median filter, was found to be ineffective and undesirable as many pixel-level land cover changes were not detected. The adaptive grey-level filtering approach showed some promise in compensating for misregistration by filling or smoothing out apparent changes resulting from the image differencing process that were caused by misregistration. However, such a misregistration compensation approach is *ad hoc* and as with image smoothing, differences associated with real land cover change may be minimized and even obscured in the process.

A common approach to compensating for misregistration is to aggregate pixels of the multi-temporal image data set to yield image arrays with larger ground resolution elements. The rationale is that the magnitude of misregistration between the multi-temporal image pair will be minimized relative to the larger land area represented by aggregated pixels (Justice et al. 1989). However, land cover changes that occur at or below the size of the original ground resolution element may not be detected after the images are aggregated.

The objectives of this Letter are to briefly: (1) derive a formal mathematical representation of the components that influence the multi-temporal image differencing process, and (2) demonstrate an approach to compensating for misregistration effects on pixel-level change assessments based on multi-temporal image data sets.

2. Multi-temporal image differencing

The most common approach to enhancing and/or quantifying image brightness change associated with land cover change is image differencing, which involves the subtraction of image brightness values on a pixel-by-pixel basis. The image brightness values may represent spectral radiance values of like waveband images or continuous value derivatives of waveband images (e.g. ratios or linear band combinations). Difference values from multiple waveband or continuous value derivative images may be combined in a multidimensional process known as ‘change vector analysis’ (Malila 1980).

The components of image brightness (*B*) that influence the temporal change between corresponding pixels of a multi-temporal image data set are represented by the terms in the following equation:

\[
\frac{\Delta B}{\Delta t} = -\frac{\Delta B}{\Delta x} D_x - \frac{\Delta B}{\Delta y} D_y + R + S
\]  

(1)

where \(\Delta B/\Delta t\) is the discrete temporal change in image brightness (\(\Delta B\)) over time interval \(\Delta t\), i.e. conventional image differencing; \(\Delta B/\Delta x\) and \(\Delta B/\Delta y\) are the spatial gradients of image brightness in the *x* and *y* directions, respectively; \(D_x\) and \(D_y\) are the magnitudes of misregistration in the *x* and *y* directions, respectively; \(R\) is the temporal difference in *B* due to radiometric effects, e.g. sensor noise, sensor calibration drift, and illumination and atmospheric differences; and, \(S\) is the temporal change in *B* resulting from actual land surface changes, i.e. the signal.

Again, image brightness (*B*), frequently called brightness value (BV), or digital number (DN), or digital count (DC), is the relative amount of reflected and/or emitted EMR received by the remote sensor or some continuous-value derivative from such remotely sensed radiation (e.g. ratio index). The variables *x* and *y*
correspond to west–east and north–south directions, respectively, for images that are geographically referenced. The origin of \( x \) and \( y \) is the upper left corner of an image array.

By rearranging equation (1), the change signal term \( S \) is isolated to yield:

\[
S = \frac{\Delta B}{\Delta t} + \frac{\Delta B}{\Delta x} D_x + \frac{\Delta B}{\Delta y} D_y - R \tag{2}
\]

Equation (2) shows that the land cover change signal can be estimated more reliably from the temporal brightness change if either misregistration and the spatial gradients of brightness along image rows and columns are negligible or both are known. It also shows that radiometric differences must be quantified or normalized in order to isolate the absolute land cover change signal from temporal differences.

3. Misregistration compensation approach

Assuming that two images of a multi-temporal pair have been radiometrically normalized and that some misregistration error exists throughout the common area of coverage for these images, more detailed and precise detection and/or quantification of land surface changes may be achieved by accounting for local spatial gradients of image brightness and subregional misregistration effects. ‘Local’ refers to the surrounding neighbourhood of image brightness values associated with a given pixel. ‘Subregional’ refers to a larger portion of the image surrounding the local neighbourhood. The premise of this compensation procedure is that misregistration effects are uniform at the local scale and the magnitude and sign of misregistration for a given subregion is nearly constant and can be estimated.

Misregistration may be compensated for by solving a numerical form of equation (2). Again, the temporal brightness gradient is calculated by differencing brightness values from each image date or:

\[
\frac{\Delta B}{\Delta t} = (B_i^{t+2} - B_i^{t+1}) \tag{3}
\]

where \( t = 2 \) and \( t = 1 \) are the later and earlier images, respectively, and \( i \) denotes the pixel of operation.

Note that \( t = 1 \) is considered the reference or base image and \( t = 2 \) is the subject image. For this paper, \( R \) is assumed to be negligible following radiometric normalization, i.e. the focus here is on compensating for misregistration effects. The computationally simplest and least biased procedure for estimating the spatial brightness gradients is to apply the central difference operator:

\[
\frac{\Delta B}{\Delta x} \text{ or } \frac{\Delta B}{\Delta y} = (B_{i+1}^{t+2} - B_{i-1}^{t+2})/2 \tag{4}
\]

where: \( i \) is incremented along rows for the \( x \) gradient and along columns for the \( y \) gradient and \( i + 1 \) is the pixel ahead, and \( i - 1 \) is the pixel behind the pixel of operation.

Here, the spatial gradients in \( x \) and \( y \) are computed for the subject image \( (t = 2) \) since its misregistration is being compensated for relative to the reference image \( (t = 1) \). The remaining two terms of equation (2) are the estimates of misregistration in \( x \) and \( y \).

There are two general approaches to estimating the magnitude of \( x \) and \( y \)
misregistration for every pixel; both of which involve surfaced or interpolating between control or match points. If the multi-temporal data set had been generated by registering one image to the other, the residuals of ground control points or automatic match points computed from the original warping function can be used to generate a surface. Another approach is to utilize automatic feature matching of the multi-temporal image pair (similar to the stereo correlation process that is commonly used in soft-copy photogrammetry), to estimate the relative offset between automatically defined match points. Resulting from either approach are two images where the value of each pixel is the x or y offset (in pixel units) of image \( t = 2 \) relative to image \( t = 1 \).

4. Empirical model testing

An empirical test of the misregistration compensation model for multi-temporal image differencing was conducted using corresponding subsets of two Landsat TM images. The test followed the design of Gong et al. (1992) who also reported preliminary findings of misregistration compensation approaches as a Letter. As for Gong et al. (1992), the testing is mostly qualitative, radiometric normalization was not attempted, and only the TM band 3 (red waveband or TM3) image was used in the test. No radiometric normalization was performed as analyses of histograms and scatterplots of the TM3 bands for both dates revealed a radiometric bias of \( B < 3 \) (i.e. relative difference between image dates less than three digital numbers).

The Landsat TM images were acquired on near-anniversary dates two years apart on 3 October 1986 and 22 September 1988 and for the same Landsat TM path-row scene that primarily encompasses San Diego County, California, USA. Both images had been rectified, georeferenced, and terrain corrected by a commercial service provider using a deterministic earth-satellite-sensor geometry model and 1:250,000-scale digital terrain data. Subsets that were 300 pixels by 300 pixels were extracted from both TM images for an area in the north-central part of the jurisdictional boundary of the City of San Diego. This study area was selected because it was predominantly covered by rural land uses in 1986 (i.e. \( t = 1 \)) and a large amount and variety of urban development occurred within the two-year interval between image acquisitions. Colour (1986) and colour infrared (1988) aerial photographs acquired originally at 1:48,000 scale were used to validate image differencing results by enabling actual versus artifactual changes to be substantiated.

Misregistration images were derived from match points generated for the image pair. Since each TM image had been geometrically corrected independent of the other, no data pertaining to residuals from a spatial registration procedure were available. The \( x \) and \( y \) differences in pixel dimensions were continuous and slowly varying ranged from \(-4.0\) to \(0.0\) pixels in both \( x \) and \( y \) dimensions with an increasing misregistration trend from top to bottom and right to left. The isotropic trend suggested an improper or inconsistent specification of the raster cell size in the original orthorectification processing of one of the images. While the misregistration trend was slowly varying, the few obvious deviations from the trend coincided with areas of greatest terrain variability.

The numerical form of equation (2) was applied using the TM band 3 (TM3) subsets and the corresponding \( x \) and \( y \) misregistration images. Equation (3) was used to calculate temporal differences and the horizontal spatial gradients were computed using the central difference gradient method of equation (4). A standard image differencing operation (i.e. equation (3)) was also applied to the multi-temporal
Figure 1. Change detection images generated from multi-temporal differencing of 3 October 1986 and 22 September 1988 TM3 subsets: (a) results from standard differencing; (b) results from misregistration compensation model. Examples of specific features associated with land cover change and artefacts are indicated by these symbols: A = agricultural development, C = cloud in 1986 image, G = graded (vegetation removed) for construction, M = misregistration artefact, R = residential development, S = cloud shadow in 1986 image, T = turf (e.g. golf course or horse track) planted since 1986.
TM3 data set to generate a change detection image (figure 1(a)) that was useful for assessing the results of the compensation model (figure 1(b)).

In general, areas of actual land use change are more distinct for the change imaged derived using the compensation model. Several examples of land use and land cover changes are marked on figures 1(a) and 1(b), as are changes resulting from clouds and cloud shadows being present in the 1986 image. False detections (artefacts) were generated by the compensation model at the edges of large areas that had been cleared for construction and were not as prevalent in the standard difference image.

Comparison of the TM3 difference images generated with and without the misregistration compensation model showed that the model reduced many small false detections in areas of no land cover change that lacked distinct linear features or sharp edges. Artefacts were also reduced in areas of heterogeneous image brightness. The model did not reduce misregistration effects where linear features and edges were present, particularly along valleys and at the boundaries of large, contrasting land cover features such as at the fringe of newly cleared land that was under construction. This linear feature and high contrast edge effect and that at the edges of areas cleared for construction are likely attributed to the use of the central difference operator, which accentuated edges unless misregistration was estimated exactly. This points to the need for a more sophisticated adjustment procedure that uses directional gradient operators.

5. Conclusions and follow-on research

The misregistration compensation model shows promise for enhancing land change features at or near the pixel scale and reducing noise caused by misregistered multi-temporal images. Sparse estimates of misregistration across the scene are combined with calculations of spatial brightness gradients to adjust the magnitude of multi-temporal image differences. Key to the success of the compensation model is the reliability and efficiency of estimating the misregistration trend. In addition to testing approaches for estimating misregistration fields, our on-going research is focusing on more complex estimates of spatial brightness gradients by incorporating the sign and magnitude of the estimated misregistration trend.

In deciding whether or not to implement the model, the cost of estimating misregistration fields and applying the numerical correction routine should be weighed against the potential information benefit pertaining to improved detection and quantification of pixel-level changes in surface cover. Implementation seems to be most appropriate for regional- to global-scale monitoring based on coarse resolution satellite data (e.g., AVHRR), where land cover changes are normally smaller than the pixel scale and misregistration can dominate multi-temporal image difference values (Bastin et al. 1995).

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References


