SEMI-AUTOMATIC REGISTRATION AND CHANGE DETECTION USING MULTI-SOURCE IMAGERY WITH VARYING GEOMETRIC AND RADIOMETRIC PROPERTIES

A. F. Habib [a], R. I. Al-Ruzouq [a], C. J. Kim [a]

[a] Department of Geomatics Engineering, University of Calgary
2500, University Drive NW, Calgary AB T2N 1N4 Canada – (Habib, Al-ruzouq)@geomatics.ucalgary.ca, Cjkim@ucalgary.ca

PS ICWG II/IV Change Detection and Updating for Geodatabase

KEY WORDS: Change Detection, Automation, Registration, Feature, Matching, Multi-resolution.

ABSTRACT:

Change detection is the process of identifying differences in the state of objects and/or phenomena under consideration by observing them at different times. Change detection is important for monitoring and managing natural resources, urban development, environmental changes, and disaster assessments. Recent advances in satellite imagery, in terms of improved spatial and temporal resolutions, allow for reliable identification and prediction of change patterns. The quality of the image registration process of the involved imagery is the key factor that dictates the validity and the reliability of the change detection outcome. The fact that change detection analysis might involve multi-spectral, multi-source, and/or multi-resolution imagery captured at different times calls for the development of a robust registration procedure that can handle these types of imageries. This paper introduces a new approach for semi-automatic image registration using linear features, which can be reliably extracted from imagery with significantly different geometric and radiometric properties. The Modified Iterated Hough Transform (MIHT) is used as the matching strategy for automatically deriving an estimate of the parameters involved in the transformation function relating the images to be registered as well as the correspondence between conjugate lines. Once the registration problem has been solved, the suggested methodology proceeds by detecting changes between the registered imagery. Traditional change detection methodologies, which are based on the subtraction of intensity images, usually fail due to different illumination conditions, sensors, and/or viewing perspectives at the moments of exposure. To overcome these problems, features that are invariant to changes in the illumination conditions can be used. Based on this reasoning, derived edges from the registered images are used as the basis for change detection in this research. Experimental results using real data proved the feasibility of the suggested approach for deriving a quantitative estimate of changes among the registered images.

1. INTRODUCTION

The demand for up-to-date geographic data is increasing due to fast changes in the real world that are taking place as a result of nature and/or human actions. Such changes have to be accurately and reliably inventoried to fully understand the physical and human processes at work (Estes, 1992). Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times (Singh, 1989). It involves the ability to quantify changes using multi-resolution, multi-spectral, and/or multi-source imagery captured at different epochs. Traditional change detection studies are based on visual/manual comparison of temporal datasets (such as satellite scenes, aerial images, maps, etc.). However, the huge flux of imagery that is being captured by an ever increasing number of earth observing satellites necessitates the development of reliable and fast change detection techniques. Such techniques are essential to reduce the high cost associated with spatial data updating activities.

Several change detection methods have been developed and reported in the literature (Singh, 1989; Townshend et al., 1992; Dowman, 1998; Bruzzone and Prieto, 2000; and Li et al., 2002). Basically, two main solutions for the change detection problem have been proposed: supervised and unsupervised approaches. The former is based on supervised classification methods, which require the availability of multi-temporal ground truth in order to derive a suitable training set for the learning process of the classifier. The latter performs change detection directly by comparing two images under consideration, without relying on any additional information (Bruzzone and Prieto, 2000).

In supervised classification, data from two images are separately classified, thus the problem of normalizing such data for atmospheric and sensor differences between two different times is minimized (Singh, 1989). The supervised approach exhibits some advantages over the unsupervised, mainly the capability to recognize the kinds of land cover transition that have occurred, robustness to different atmospheric and light conditions at the two acquisition times, and the ability to process multi-sensor/multi-source images (Bruzzone and Serpico, 1997). A major drawback of the supervised classification is that the generation of an appropriate multi-temporal ground truth is usually a difficult and expensive task; in addition, greater computational and labelling efforts are required. On the other hand, unsupervised classification primarily entails the creation of “difference images”. It involves image differencing, image ratio, vegetation index differencing, image regressions, change vector analysis (CVA), and principal component analysis (PCA). Changes are then identified through analysis of (e.g., thresholding) the difference images.

Based on the literature of change detection techniques, the following issues have to be considered:

- Image differencing methods assume that the differences between the radiometric values are due to changes in the object space. Indeed these differences could be a result of other factors, such as different atmospheric conditions, illumination conditions, changes in soil moisture and sunlight angle. Several solutions were suggested to overcome such a problem. Basically, these solutions depend on image enhancement and radiometric corrections that tend to reduce radiometric differences between images under consideration.
- Most of these methods require a decision as to where to place the threshold boundaries in order to separate the areas of changes from those of no change (Singh, 1989). In fact, classical techniques perform thresholding based on empirical strategies or manual trial and error procedures, which significantly affect the reliability and the accuracy of the final change detection results (Li et al., 2002).
- In general, classification methods require two or more bands for the classification process. This is not always available especially when dealing with aerial images that represent an important source of historical information needed for change detection purposes.
- Image differencing techniques are sensitive to misregistration between the reference and input images (Singh, 1989; Townshend et al., 1992; Li et al., 2002;). Literature pointed out that accuracy of the image registration process is the key factor that controls the validity and reliability of the change detection outcome.

In summary, uncertainty in the change detection outcome relies on two factors. Firstly, the detected changes might be biased by inaccurate rectification/registration procedure (geometric differences). Secondly, it is affected by possible radiometric differences due to atmospheric changes and/or different sensor types. To overcome the problem of geometric differences, this study will investigate and develop a semi-automated, accurate, and robust registration paradigm that guarantees accurate co-registration which is required for reliable change detection (Section 2). To overcome the problem of radiometric differences, derived edges from the registered images are used as the basis for change detection. The utilization of edges is motivated by the fact that they are invariant with respect to possible radiometric differences between the images in question (Section 3). Section 4 demonstrates the proposed methodology of change detection. Experimental results using real data, which proves the feasibility and robustness of the suggested methodology, are discussed in Section 5. Finally, conclusions and recommendations for future work are discussed in Section 6.

2. GEOMETRIC DIFFERENCES

High resolution overlapping scenes captured by space-borne platforms and aerial images are becoming more available at a reasonable cost. These images represent the main source of recent and historical information that are necessary for change detection application. Due to different imaging systems, spatial resolutions, viewing points and perspective geometry between these temporal images, geometric differences should be expected. Reliable change detection is contingent on accurate compensation of these differences among the involved images. The proposed registration methodology will accurately align the images in question regardless of possible geometric differences.

In general, an image registration process aims at combining data and/or information from multiple sensors in order to achieve improved accuracies and better inference about the environment than could be attained through the use of a single sensor. An effective automated image registration methodology must deal with four issues (Habib and Al-Ruzouq, 2004); namely registration primitives, transformation function, similarity measure, and matching strategy. The following subsections briefly discuss the rationale regarding these issues.

2.1 Registration primitives

To carry out the registration process, a decision has to be made regarding the choice of the appropriate primitives (for example, distinct points, linear features, or homogeneous regions). In this research, straight-line segments are used as the registration primitives. This choice is motivated by the following facts:

- Straight lines are easier to detect than distinct points and areal features. Moreover, the correspondence between conjugate linear features in the input imagery becomes easier.
- Images of man-made environments are rich with straight-line features.
- It is straightforward to develop mathematical constraints (similarity measures) ensuring the correspondence of conjugate straight-line segments.
- Free-form linear features can be represented with sufficient accuracy as a sequence of straight-line segments (poly-lines).

After selecting straight-line segments as the registration primitives, one has to make a decision regarding on how to represent them. In this research, the line segments are represented by their end points. This representation is chosen since it is capable of representing all line segments in 2-D space. Also, it will allow for a straightforward similarity measure that mathematically describes the correspondence of conjugate line segments. It should be mentioned that the end points defining corresponding line segments in the imagery need not be conjugate, Figure 1.

2.2 Registration transformation function

The second issue in a registration procedure is concerned with establishing the transformation function that mathematically describes the mapping function between the imagery in question. In other words, given a pair of images, reference and input images, the transformation function will attempt to properly overlay them. Habib and Morgan (2002) showed that affine transformation, Equation 1, could be used as the registration transformation function for imagery captured by satellite imaging systems with narrow angular field of view over relatively flat terrain (a terrain with negligible height variations compared with the flying height).

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} a_0 \\ b_0 \end{bmatrix} + \begin{bmatrix} a_1 & a_2 \\ b_1 & b_2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \tag{1}$$

where

$(x\ ,\ y\ )$: coordinate of a point in the reference image

(x', y'): coordinate of the conjugate point in the input image

$(a_0, \ldots b_2)$ affine transformation parameters.

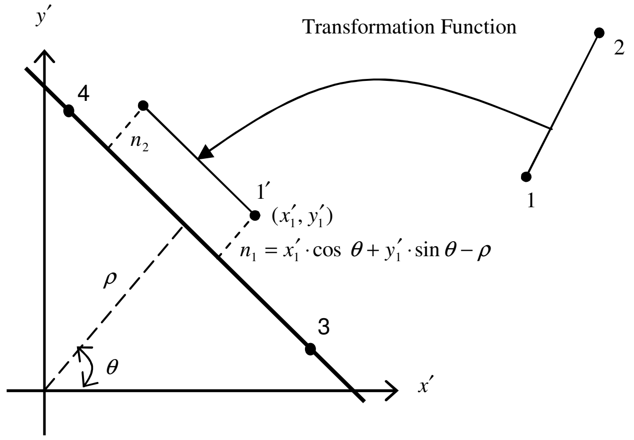

Figure 1. Similarity measure using straight-line segments

2.3 Similarity measure

The next step in the registration paradigm is the selection of the similarity measure, which mathematically describes the necessary constraints for ensuring the correspondence of conjugate primitives. The similarity measure formulation depends on the selected registration primitives and their respective attributes. As mentioned before, the registration primitives, straight-lines, will be represented by their end points, which need not be conjugate.

Assuming that a line segment (1-2) in the reference image corresponds to the line segment (3-4) in the input image, Figure 1, the similarity measure should mathematically describe the fact that the line segment (1-2) will coincide with the corresponding line segment (3-4) after applying the transformation function relating the reference and input images. Such a measure can be derived by forcing the normal distances between the end points of a transformed line segment in the reference image, and the corresponding line segment in the input image to be zero (i.e., $n_1 = n_2 = 0$, Figure 1). Equation 2 mathematically describes such a constraint for one of the end points of the line segment in the reference image.

$$x_1' \cos\theta + y_1' \sin\theta - \rho = 0 \qquad (2)$$

where

(ρ, θ) Polar coordinates representing the line segment (3-4) in the input image

(x_1', y_1') Transformed coordinates of point 1 in the reference image after applying the registration transformation function.

Another constraint in the form of Equation 2 can be written for point 2 along the line-segment in the reference image.

2.4 Matching strategy

To automate the solution of the registration problem, a controlling framework that utilizes the primitives, similarity measure, and transformation function must be established. This framework is usually referred to as the matching strategy. In this research, the MIHT is used as the matching strategy. Such a methodology is attractive since it allows for simultaneous matching and parameter estimation. Moreover, it does not require complete correspondence between the primitives in the reference and input images. MIHT has been successfully implemented in several photogrammetric operations such as automatic single photo resection and relative orientation (Habib et al, 2001a, 2001b).

MIHT assumes the availability of two datasets where the attributes of conjugate primitives are related to each other through a mathematical function (similarity measure incorporating the appropriate transformation function). The approach starts by making all possible matching hypotheses between the primitives in the datasets under consideration. For each hypothesis, the similarity measure constraints are formulated and solved for one of the parameters in the registration transformation function. The parameter solutions from all possible matching hypotheses are stored in an accumulator array, which is a discrete tessellation of the expected range of the parameter under consideration. Within the considered matches, correct matching hypotheses would produce the same parameter solution, which will manifest itself as a distinct peak in the accumulator array. Moreover, matching hypotheses that contributed to the peak can be tracked to establish the correspondence between conjugate primitives in the involved datasets. Detailed explanation of the MIHT can be found in Habib et al, 2001b.

The basic steps for implementing the MIHT for solving the registration problem are as follows:

- Approximations are assumed for the parameters which are yet to be determined. The cell size of the accumulator array depends on the quality of the initial approximations; poor approximations will require larger cell sizes.
- All possible matches between individual registration primitives within the reference and input images are evaluated, incrementing the accumulator array at the location of the resulting solution, pertaining to the sought-after parameter, from each matching hypothesis.
- After all possible matches have been considered, the peak in the accumulator array will indicate the most probable solution of the parameter in question. Only one peak is expected for a given accumulator array.
- After each parameter is determined (in a sequential manner), the approximations are updated. For the next iteration, the accumulator array cell size is decreased to reflect the improvement in the quality of the parameters. Then, the above two steps are repeated until convergence is achieved (for example, the estimated parameters do not significantly change from one iteration to the next).
- By tracking the hypothesized matches that contribute towards the peak in the last iteration, one can determine the correspondence between conjugate primitives. These matches are then used in a simultaneous least squares adjustment to derive a stochastic estimate of the involved parameters in the registration transformation function.

Once the registration primitives, transformation function, similarity measure, and the matching strategy have been selected, they are integrated in an automatic registration procedure. As mentioned earlier the accuracy of the registration process is the key factor that controls the validity and the reliability of the change detection outcome. Section 5 will show that a few pixels accuracy has been achieved.

3. RADIOMETRIC DIFFERENCES

The basic premise in using remotely sensed data for a change detection application is that changes in land cover will result in changes in radiance values. Moreover, changes in radiance due to land cover changes must be larger when compared to radiance changes caused by other factors. These other factors might include differences in atmospheric conditions, sun angle and soil moisture. One should expect that these factors will affect the reliability of change detection algorithms especially when considering images captured by different sensors that have varying radiometric and spatial resolutions.

To alleviate the effect of these factors, intensity normalization is traditionally used as a pre-processing technique to compensate for possible illumination variations between the involved images. In this type of pre-processing, the intensity values in the second image are normalized to have the same mean and variance values as those in the first image. Assuming that the involved images are co-registered relative to a common reference frame, one can proceed by applying image-differencing methods to create a new image that represents the changes. The comparison results are based on the assumption that the differences between the radiometric properties of corresponding pixels are due to actual changes in the object space. However, these differences could be the result of other factors, such as different atmospheric conditions, noise, different imaging sensors, and/or registration/rectifications errors. Moreover, the difference image is usually binarized by thresholding where thresholds are empirically selected. In these cases, traditional approaches to change detection, which are based on the differencing of intensity images, fail.

To overcome these problems, derived edges from the registered images are used as a basis for the proposed change detection methodology. The utilization of edges is motivated by the fact that they are invariant with respect to possible radiometric differences between the images in question.

4. CHANGE DETECTION METHODOLOGY

The proposed method for change detection is as follows:

- Resample the input image into the reference frame associated with the reference image. The parameters of the registration transformation function (Section 2) are used in the resampling process. After resampling, corresponding pixels are assumed to belong to the same object space feature.
- Apply intensity normalization techniques to the images in question (e.g., to ensure that they have the same intensity mean and variance values) in order to reduce the radiometric differences between the involved images. However, this procedure would not be enough to eliminate radiometric differences in the involved images.
- Extract edge cells from the resampled images using the canny edge detector (Canny, 1986). Utilizing the edge images has two advantages. First, derived edges are robust to possible radiometric differences between the registered images (e.g., due to noise and/or different spectral properties). Also, the edges would correspond to interesting features (e.g., building boundaries, roads, trails, etc.). Therefore, comparing edge images will be useful in outlining the amount of urbanization activities, which is one of the most important objectives of change detection exercises. The final output of the edge extraction process will be binary images in which white pixels refer to edges while black pixels refer to non-edges.
- Apply the majority filter (also known as the mode filter) to the edge images. This filter is applied to binary images where a window is centered at each pixel and the value of this pixel is changed or maintained according to the majority of the pixels within this window (Lillesand and Kiefer 2000). In the proposed methodology for change detection, the majority filer has been implemented for the following reasons:
  - To compensate for small registration errors (in the order of few pixels).
  - To balance the effect of varying edge densities in the registered images especially when dealing with multi-source images.
  - To fill small gaps within an area with numerous edges (Figure 2-a, highlighted by solid circles), and smooth object boundaries without expanding and/or shrinking the objects (Lillesand and Kiefer 2000).
  - To eliminate isolated edges (Figure 2-b, highlighted by dotted circles).

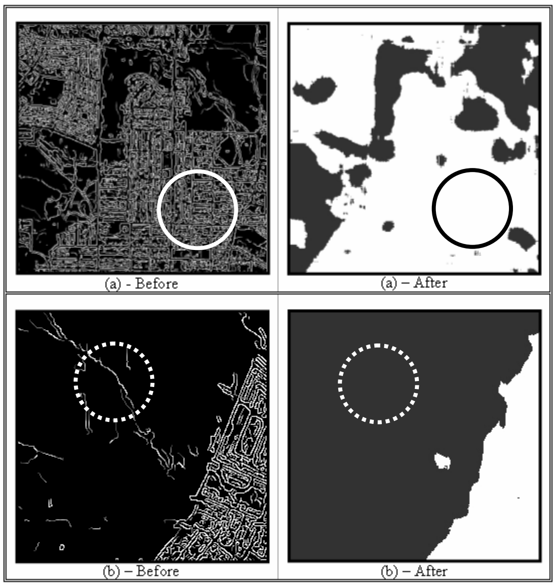

Figure 2. Majority filter: filling gaps among dense edges (a), removing isolated edges (b)

As a result, filtered images will highlight areas with interesting features since they lead to a dense distribution of edge cells.

- Subtract filtered images (pixel-by-pixel) in order to highlight areas of change.
- Apply a majority filter to the difference image to eliminate small areas (since changes/no-changes are expected to be locally spread – i.e., they are not isolated).

5. EXPERIMENTAL RESULTS

Experiments have been conducted using multi-source, multi-resolution, and multi-temporal imageries over the city of Calgary, Alberta to illustrate the feasibility of the suggested methodology. The experiments incorporated a 1374 rows by 1274 columns aerial photo (5.0m resolution) captured in 1956, 1374 rows by 1274 columns aerial photo (3.5m resolution) captured in 1972, 2000 rows by 2000 columns ortho-image (5.0m resolution) created from an aerial image captured in

1999, and 300 rows by 300 columns LANDSAT image (30m resolution) captured in 2001. These scenes exhibit significantly different geometric and radiometric properties. Straight-line segments have been manually digitized in these images. As an example, Figure 3 shows the digitized segments in the 1999 ortho-photo and 1956 aerial image, where 139 lines have been digitized in the reference image (1956 aerial) and 183 Lines have been digitized in the input image (1999 ortho-photo).

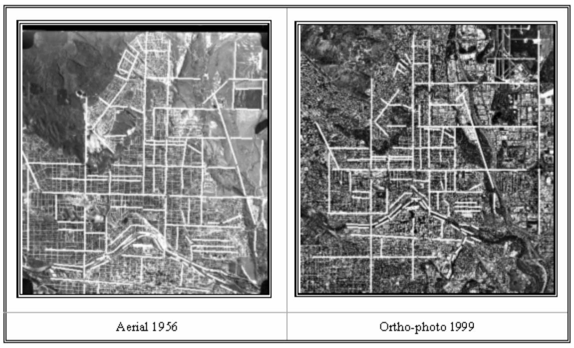

Figure 3. Digitized linear features in the 1956 aerial image and the 1999 ortho-photo

A closer look at Figure 3 reveals that there is no complete correspondence between the digitized lines in the input and reference images. The digitized segments were then incorporated in the MIHT strategy to determine the parameters involved in the registration transformation function as well as the correspondence between conjugate line segments.

The estimated parameters for affine transformation functions and their variance components for the abovementioned datasets are listed in Table 1. The estimated variance components, which reflect the quality of fit, reveal two facts. First, they show good registrations between the involved images (within a few pixels). Also, the small variance components signify the validity of the affine transformation as the registration transformation function.

Affine	Aerial_56/ Aerial_72	Aerial_56/ Ortho_99	Aerial_56/ Land_01
$\hat{\sigma}_o^2$ (Pixel ^2)	$\mathbf{2.9524}^{\wedge 2}$	$\mathbf{2.1537}^{\wedge 2}$	$\mathbf{1.8822}^{\wedge 2}$
a_o (pixel)	-78.9282	-105.8868	41.3663
a_1	1.4148	1.0899	00.1753
a_2	-0.0925	-0.0235	00.0493
b_o (pixel)	415.1431	614.5326	53.0329
b_1	00.099324	0.0292	-00.0481
b_2	1.4242	1.0916	00.1754

Table 1. Affine transformation parameters between the involved datasets

In addition to the estimated parameters, the correspondences between line segments have been identified. For example, Figure 4 depicts established correspondences between the digitized primitives in the 1956 aerial image and the 1999 ortho-photo. A mosaic image covering the northwest part of the city is derived by combining the 1999 ortho-photo and the 1956 aerial image, where every other square patch in the reference image has been replaced by the corresponding resampled patch in the input image, is shown in Figure 5. It can be seen that features (for example, roads, rivers) in the derived mosaic fit each other (observe the smooth transition along the features within the resampled patches). A closer look at Figure 5 reveals the changes that took place in the northwest part of the city during the forty three years between the moments of capture.

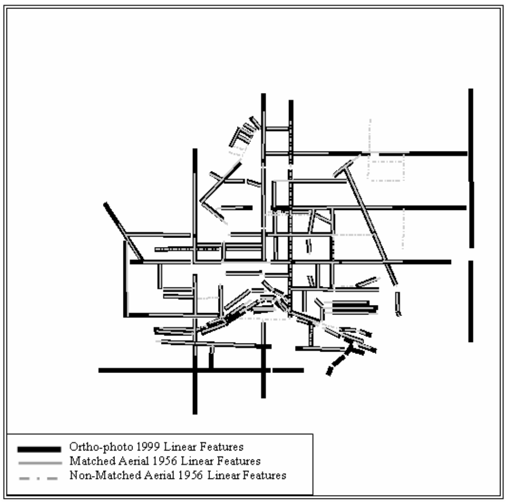

Figure 4. Established correspondences between the 1956 aerial image and the 1999 ortho-photo line segments

Figure 5. 1956 aerial image and 1999 ortho-photo mosaic

Having established the transformation function between the images, the input image can be resampled into the reference frame associated with the reference image. As explained in the previous section, the resampling is followed by applying Canny edge detection and majority filter to both images. Then, the resulting images are subtracted to produce a change image, which is enhanced by re-application of the majority filter. Figure 6-a shows the change image resulting from the registration of the 1956 aerial image with the 1999 ortho-photo. In this image, white areas indicate changes while black areas indicate parts with no change. Simple statistics show that there is roughly 50.6% change between the 1956 and 1999 imagery. Dividing the area into four quarters shows that the percentages of change, which occurred in the northwest, northeast, southeast and southwest parts of the image, are 74.8%, 66.4%, 34.4%, and 26.8%, respectively. The sub-images (b, c, d, and e) in Figure 6 show different types of changes that took place. Sub image 6-b shows changes as a result of an urbanization activity (new residential community has been built). Sub image 6-c shows changes caused by trails in newly developed parks. Changes resulting from the construction of a new highway along the east side of the city is shown in sub image 6-d.

Finally, sub image 6-e shows changes due to different shadowing effects caused by newly erected high-rise buildings in the downtown area.

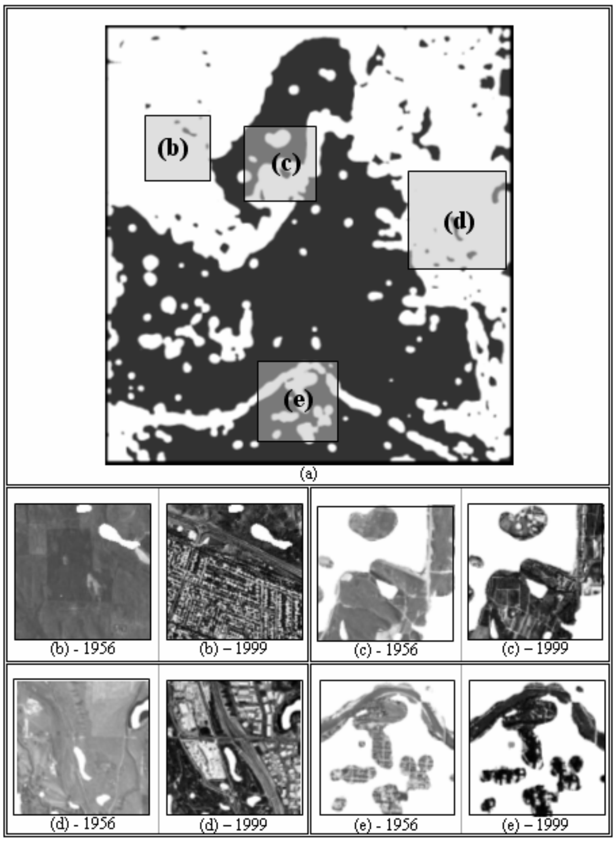

Figure 6. Change detection image (a), white pixels represent changes. Sub-figures b, c, d, and e have been cropped and closely examined

6. CONCLUSION AND RECOMMENDATIONS

This paper presents a new methodology for image registration together with a suggested procedure for detecting changes between the involved images. The developed approach has been tested on real datasets, which showed its effectiveness in registering and detecting changes among multi-source, multi-resolution, and multi-temporal imagery.

The use of the MIHT procedure, for automatic registration of multi-source imagery with varying geometric and radiometric properties, has been explained. The presented approach used linear features (straight-line segments) as the registration primitives since they can be reliably extracted from the images. The MIHT sequentially solves for the parameters involved in the registration transformation function while establishing the correspondence between conjugate primitives. Experimental results using real data proved the feasibility and the robustness of the MIHT strategy even when there was no complete correspondence between conjugate lines in the images. This robustness is attributed to the fact that the parameters are estimated using common features in both datasets while non-corresponding entities are filtered out prior to the parameter estimation.

To avoid the effect of possible radiometric differences between the registered images, due to different atmospheric conditions, noise, and/or different spectral properties, the change detection is based on derived edge images. The use of edge images is attractive since it would lead to an effective detection of urbanization activities as they are represented by a dense distribution of edge cells. Also, a majority filter is applied to compensate for small registration errors as well as eliminate small gaps and isolated edges. The images are then subtracted to produce a change image, which could be enhanced by applying a majority filter to remove small regions. The change detection results were found to be consistent with those visually identified.

Future research will concentrate on automatic extraction of the registration primitives, straight-line segments, from the input imagery. Moreover, the origin of the detected changes will be investigated (e.g., new residential community, new roads, etc.).

7. REFERENCES

Bruzzone, L., and D. Prieto, 2000. Automatic analysis of the difference image for unsupervised change detection, *IEEE Transactions on Geoscience and Remote Sensing*, 38(3):pp. 1171-1182.

Bruzzone, L., and S. Serpico, 1997. An iterative technique for the detection of land-cover transitions in multitemporal remote sensing images, *IEEE Transactions on Geoscience and Remote Sensing*, 35(4):pp. 858-867.

Canny, J., 1986. A computational approach to edge detection, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 6(6):pp. 679-698.

Dowman, I., 1998. Automated procedures for integration of satellite images and map data for change detection: The archangel project, *GIS-between visions and applications*. IAPRS, 32(4):pp. 162-169.

Estes, J., 1992. Technology and policy issues impact global monitoring, *GIS world*, 5(10): pp.52-55

Habib, A., and M. Morgan, 2002. Epipolar image resampling from push-broom imagery: investigation and preliminary implementation, *Korean Electronics and Telecommunications Research Institute (ETRI)*, Daejeon, Korea, 107 p.

Habib, A., and R. Al-Ruzouq, 2004. Line-based modified iterated Hough transform for automatic registration of multi-source imagery, *Photogrammetric Record*, 19(105):pp. 5–21.

Habib, A., M. Morgan, and Y. Lee, 2001a. Integrating data from terrestrial mobile mapping systems and aerial imagery for change detection purposes, *Proceedings of the Third Mobile Mapping Symposium,* 3-5 January, Cairo, Egypt, unpaginated CD-ROM.

Habib, A., Y., Lee, and M. Morgan, 2001b. Surface matching and change detection using modified iterative Hough transform for robust parameter estimation, *Photogrammetric Record*, 17 (98):pp. 303-315.

Li, D., S. Haigang, and X. Ping, 2002. Automatic change detection of geo-spatial data from imagery. *Mapping and Remote Sensing,* commission II, IC WG II/ IV:pp. 245-252.

Lillesand, T., and R. Kiefer. 2000. *Remote sensing and image interpretation*, 4thed. John Wiley and Sons, New York, 724 p.

Singh, A., 1989. Digital change detection techniques using remotely-sensed data, *International Journal of Remote Sensing*, 10(6):pp. 989-1003.

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