

Semi-Automatic Registration of Multi-Source Satellite Imagery with Varying Geometric Resolutions

Ayman Habib and Rami Al-Ruzouq

Abstract

Image registration is concerned with the problem of how to combine 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. Registration of imagery and information from multiple sources is essential for a variety of applications in remote sensing, medical diagnosis, computer vision, and pattern recognition. In general, an image registration methodology must deal with four issues. First, a decision has to be made regarding the choice of primitives for the registration procedure. The second issue is concerned with establishing the registration transformation function that mathematically relates geometric attributes of corresponding primitives. Then, a similarity measure should be devised to ensure the correspondence of conjugate primitives. Finally, a matching strategy has to be designed and implemented as a controlling framework that utilizes the primitives, the similarity measure, and the transformation function to solve the registration problem. This paper outlines a comprehensive investigation and implementation of the involved issues in a semi-automatic registration procedure capable of handling multi-source satellite imagery with varying geometric resolutions.

Introduction

Image registration aims at geometrically aligning two or more images so that corresponding pixels and their derivatives (edges and corner points) representing the same underlying structure in object space may be integrated or fused. In some applications, image registration is the final goal (e.g., interactive remote sensing and medical imaging) and in others, it is a prerequisite for accomplishing high-level tasks such as sensor fusion, surface reconstruction, change detection, and object recognition. The enormous increase in the volume of remotely sensed data that is being acquired by an ever-growing number of earth observation satellites (e.g., Ikonos, SPOT-5, Landsat-7, Quickbird, Orbview, EROS-A1) mandates the development of accurate, robust, and automated registration procedures that can handle imagery with varying geometric and radiometric properties.

The need for developing a reliable registration methodology is motivated by the fact that its application areas span the following fields (Brown, 1992):

- Remotely sensed data processing for military and civilian applications in agriculture, geology, oceanography, oil, mineral exploration, pollution control, urban expansion monitoring, forestry, and target location and identification.
- Medical image analysis for diagnosis purposes such as tumor detection and disease localization. Image registration can be also useful for biomedical applications, such as, classification of microscopic images of blood cells, cervical smears, and chromosomes.
- Computer vision and pattern recognition applications such as segmentation, object recognition, shape reconstruction, motion tracking, stereo mapping, change detection, and character recognition.

Automatic and manual registration of imagery remains challenging for several reasons. First, images from different sensors usually have their own inherent noise. Furthermore, radiometric, as well as geometric properties of the same object in the involved imagery, might differ as a result of changes in the sensor view point, imaging methodology, imaging conditions (e.g., atmospheric changes, cloud coverage, and shadows), and spectral sensitivity of the involved imaging systems (e.g., panchromatic, multi-spectral and hyper-spectral imaging systems). Finally, the registration process can be complicated by changes in object space caused by movements, deformations, and urban development between the epochs of capture associated with the involved images.

Traditional procedures for manually registering an image pair require interactive selection of tie points in each image. The points are then used to determine the parameters of a registration transformation function, which is subsequently used to resample one of the images into the reference frame associated with the other image. However, such a procedure can lead to inaccurate results and is slow to execute, especially if a large number of images with varying geometric and radiometric properties need to be registered (Figure 1).

Automation of the registration procedure requires the replacement of manual tie point selection with automatic algorithms for locating corresponding points in both images

University of Calgary, Department of Geomatics Engineering,
2500 University Drive, NW, Calgary, Canada T2N 1N4
(habib@geomatics.ucalgary.ca; al-ruzouq@geomatics.
ucalgary.ca).

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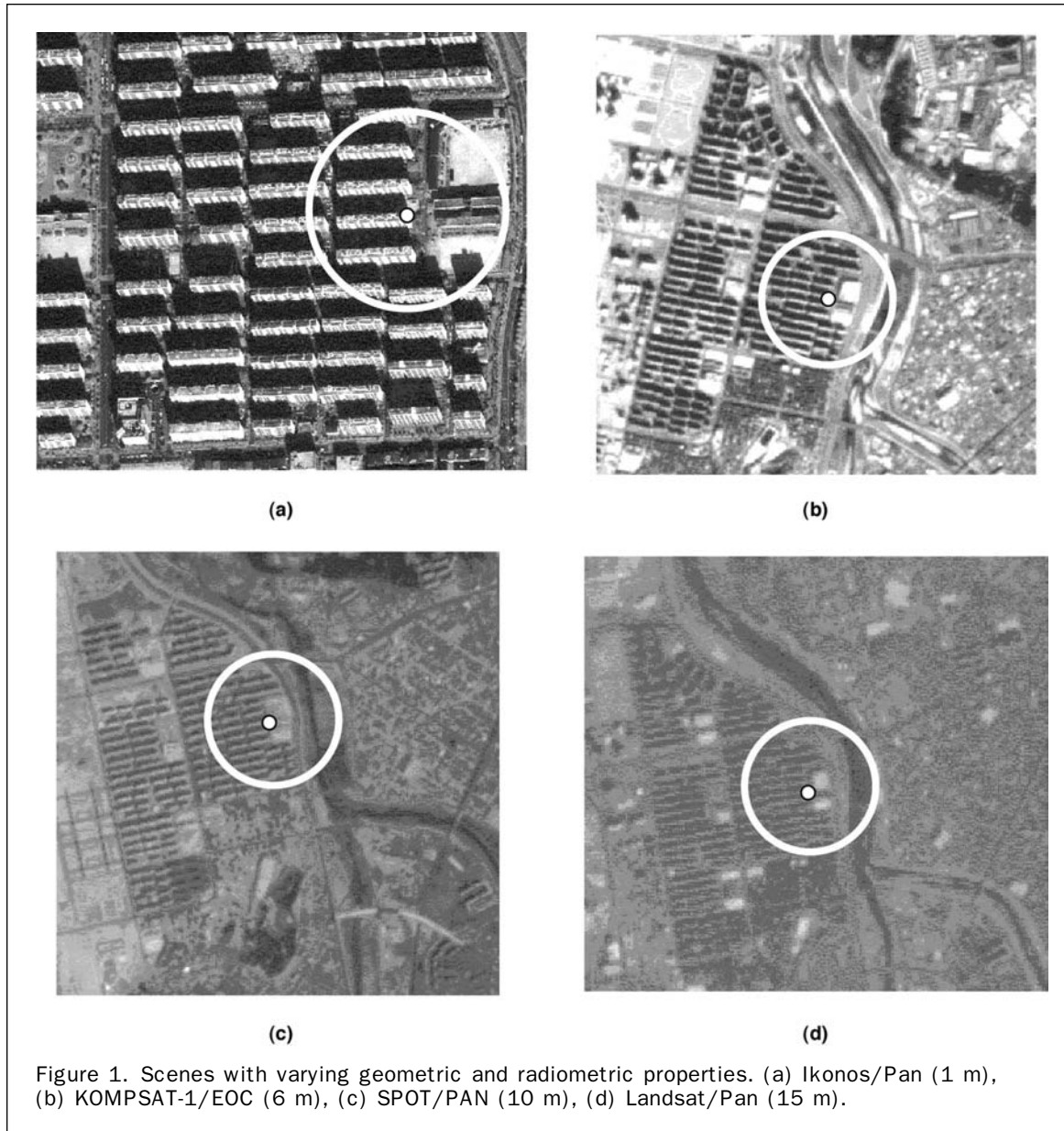


Figure 1. Scenes with varying geometric and radiometric properties. (a) Ikonos/Pan (1 m), (b) KOMPSAT-1/EOC (6 m), (c) SPOT/PAN (10 m), (d) Landsat/Pan (15 m).

(Brown, 1992). Points can be automatically extracted using an interest operator (Förstner and Gulch, 1987; Moravec, 1977). Then, extracted points can be automatically matched by considering the radiometric properties of the surrounding pixels and the geometric distribution of the whole set of selected points across the entire image (Boardman *et al.*, 1996). Needless to say, extracted points from multi-source imagery with varying radiometric and geometric properties will be difficult to match. Moreover, for this imagery it would be unlikely that point extraction algorithms are able to identify the same point. One could even argue that manual registration of such imagery using points will be extremely difficult. For example, visually inspecting the imagery in Figure 1, one can see that manual identification of conjugate points is extremely difficult, if not impossible. Therefore, it is clear that points are not suitable primitives when the images to be registered have significantly different geometric and radiometric properties.

Consequently, linear and areal features are more suited for multi-source image registration since the geometric

distribution of the pixels making up the feature can be used in the matching, rather than their radiometric attributes. Linear features can be extracted using derivative-based edge detectors (Pratt, 1991) or line extraction algorithms such as Hough transform (Hough, 1962). On the other hand, areal features (patches) can be extracted using classification and segmentation algorithms (Gonzalez and Woods, 1992). A vast body of literature focused on automatic image registration by matching point and areal primitives using a cost function involving the radiometric and/or geometric properties of these features (Dare and Dowman, 2001; Thepaut *et al.*, 2000; Hsieh *et al.*, 1997; Li *et al.*, 1995; Wolfson, 1990). These methods have certain advantages in computing the transformation parameters in a single step and in retaining the traditional way of thinking about registration in the sense of identifying similar features first, and then computing the parameters of the registration transformation function. However, they have considerable drawbacks in meeting the current challenges of image registration. First, the developed similarity measures for

matching those primitives are empirical and sometimes subjective. Also, the involved imagery has to be approximately aligned and registered prior to the automatic registration procedure to avoid ambiguities in matching the involved primitives. In addition, areal primitives might not be always available especially when dealing with satellite scenes over urban areas. Finally, registration procedures based on areal primitives use the center of gravity of these features as the registration primitives. The estimated centers of gravity are susceptible to potential errors associated with the identified boundaries of these patches.

Seedahmed and Martucci (2002) introduced an automatic registration procedure that has been largely based on the Modified Iterated Hough Transform (MIHT) strategy (Habib *et al.*, 2001a, b). The suggested approach by Seedahmed and Martucci significantly differs from the abovementioned registration strategies as it simultaneously determines the correspondence between the involved primitives and solves for the parameters of the registration transformation function. However, this work starts by extracting point primitives, which cannot be reliably extracted from imagery with different geometric and radiometric properties. A common characteristic of all prior research in this area is that the registration transformation function is not investigated (i.e., simplified and sometimes invalid registration transformation function is assumed).

This research aims at developing a registration methodology for handling recently available satellite imagery with varying geometric and radiometric properties (e.g., Ikonos, SPOT-5, Landsat-7, Quickbird, Orbview, and EROS-A1). This paper describes in detail the essential components and the suggested implementation of an effective image registration methodology, which includes selecting appropriate primitives, transformation function, similarity measure, and matching strategy. Afterwards, experimental results involving satellite imagery with varying radiometric and geometric properties are discussed. Finally, conclusion and recommendation for future work are presented.

Image Registration Paradigm

The following subsections explain the devised methodologies and the authors' rationale behind the registration primitives and their representation, transformation functions, similarity measures, as well as matching strategy.

Registration Primitives

The registration primitives encompass the domain in which information is extracted from input imagery for the registration process (distinct points, linear features, and homogenous/areal regions). For multi-resolution scenes, linear features are the most appropriate primitives since they can be reliably identified and matched in the input imagery. This is not the case for point primitives, where conjugate points are difficult to identify even manually (Figure 1). On the other hand, areal primitives might not be always available especially when dealing with scenes over urban areas. In summary, utilizing linear features is motivated by the following facts:

- For multi-source imagery with varying geometric and radiometric resolutions, the texture and grey levels at the location of conjugate points will not likely be similar. Consequently, automatically and manually extracted points will be difficult to match.
- Linear features can be considered as a dual representation of areal features through the use of their boundaries. Compared to areal features, linear features are more appropriate for change detection applications, since they can be broken into smaller subsets, which can be individually matched. However, dividing an areal feature into smaller subsets is not a trivial task.

- Compared to distinct points, linear features have higher semantics, which can be useful for subsequent processes (such as DEM generation, map compilation, change detection, and object recognition).
- Images of man-made environment are rich with linear features
- It is easier to automatically extract linear features from imagery rather than distinct points (Kubik, 1991).
- Geometric constraints are more likely to exist among linear features which can lead to a simple and robust registration procedure.

Linear features can be represented either by an analytical function (e.g., straight lines, conic sections, or parametric functions) or a free form shape. In this research, straight-line segments have been chosen as the registration primitives for the following reasons:

- Straight lines are easier to detect and the correspondence problem between conjugate features in the input imagery becomes easier.
- It is straightforward to develop mathematical constraints (similarity measures) describing the correspondence of conjugate straight-line segments.
- Free-form linear features can be represented with sufficient accuracy as a sequence of straight-line segments (polylines).

After selecting straight-line segments as the registration primitives, one has to make a decision regarding how to represent them. In this research, the line segments will be represented by their end points. This representation is chosen since it will have no singularity (i.e., it is capable of representing all line segments in 2D space). One should note that the end points defining corresponding line segments in the imagery need not be conjugate (Figure 2).

Registration Transformation Function

At this stage, one should establish the transformation function that mathematically relates the constituents of the involved image pair in the registration procedure. In other words, given a pair of images (reference and input images), the registration process attempts to find the relative transformation between the images. The type of spatial transformation needed to properly overlay the input and reference images is one of the most fundamental and difficult tasks in any image registration technique. Such difficulty can be attributed to the facts that images involved in the registration process might have been taken from different viewpoints, under different conditions, using different imaging technologies, or at different times. The registration transformation

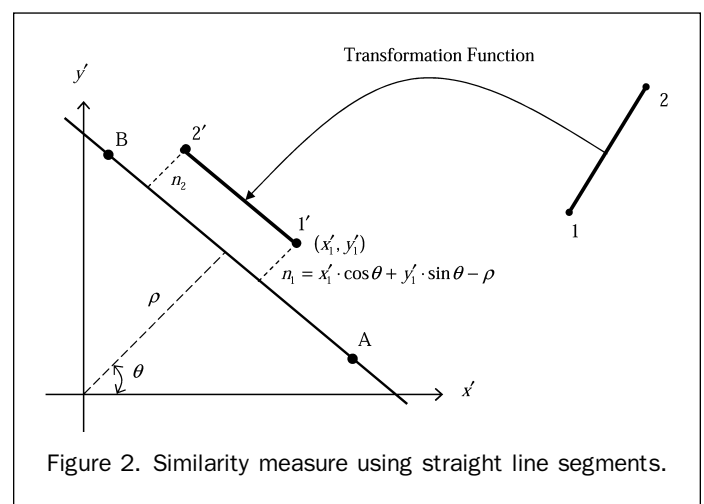


Figure 2. Similarity measure using straight line segments.

function must be applicable to multi-resolution images that might have been captured under different circumstances. Throughout this paper, (x,y) denotes the coordinates of a point in the reference image and (x',y') is used for the coordinates of the conjugate point in the input image.

The image formation process can be described by a central (perspective) projection where the projection rays from the object to the image space pass through a single point, i.e., the perspective center. The rigorous mathematical relationship between the loci of conjugate points in images captured according to perspective projection can be described by the co-planarity condition, which describes the mathematical relationship between a selected point in the reference image and the corresponding epipolar line in the input image (Habib and Kelley, 2001b). For images captured by either frame or line cameras, there is no closed form that describes the mathematical relationship between conjugates points due to expected variations in the object space elevation. However, such transformation can be established if and only if a DEM of the object space is available which is not typically the case.

There has been an increasing trend within the photogrammetric community for using approximate models to describe the mathematical relationship between image and object space points. For scenes captured by high altitude line cameras with narrow angular field of view (e.g., Ikonos, SPOT, Landsat, EROS-A1, Quickbird, and Orbview), parallel projection can be used to approximate the mathematical relationship between image and object space coordinates (Habib and Morgan, 2002). For relatively planar object space (i.e., height variation within the object space is very small compared to the flying height), the parallel projection can be simplified to an affine transformation involving six parameters. Due to the transitive property of an affine transformation, the relationship between corresponding coordinates in the input and reference images can be represented by an affine transformation as well (Hanley and Fraser, 2001). For situations where the image is almost parallel to the object space, the affine transformation function can be further approximated by a 2D similarity transformation.

Since this paper is focusing on registering multi-resolution satellite imagery, affine and 2D similarity transformation functions will be used to establish the mathematical relationship between the elements of the involved image-pair. After discussing the choice of the most appropriate registration primitives as well as the transformation function between the reference and input images, one can proceed to the third issue of the registration paradigm: the similarity measure.

Similarly Measure

The similarity measure, which mathematically describes the coincidence of conjugate line segments after applying the registration transformation function, incorporates the attributes of the registration primitives to derive the necessary constraint(s) that can be used to estimate the parameters of the transformation function relating the reference and input images. In other words, having two datasets, which represent the registration primitives (straight-line segments) that have been manually or automatically extracted from the input and reference images, one should derive the necessary constraints to describe the coincidence of conjugate primitives after applying the appropriate registration transformation function.

Assume that we have a line segment (12) in the reference image, which corresponds to the line segment (AB) in the input image (Figure 2). As mentioned earlier, the end points of the two segments need not be conjugate. The similarity measure should mathematically describe the fact

that the line segment (12) will coincide with the corresponding line segment (AB) 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 line segment in the reference image, after applying the transformation function, and the corresponding line segment in the input image to be zero (i.e., $n_1 = n_2 = 0$, Figure 2). Equation 1 mathematically describes such a constraint for one of the end points of the line segment in the reference image:

$$x'_1 \cdot \cos\theta + y'_1 \cdot \sin\theta - \rho = 0 \quad (1)$$

where, (ρ, θ) are the polar coordinates representing the line segment AB in the input image, and (x'_1, y'_1) are the transformed coordinates of point 1 in the reference image after applying the registration transformation function.

The mathematical relationship between (x_1, y_1) and (x'_1, y'_1) can be described either by Equations 2 or 3 depending on whether we choose affine or 2D similarity registration transformation function, respectively.

$$\begin{bmatrix} x'_1 \\ y'_1 \end{bmatrix} = \begin{bmatrix} a_0 \\ b_0 \end{bmatrix} + \begin{bmatrix} a_1 & a_2 \\ b_1 & b_2 \end{bmatrix} \begin{bmatrix} x_1 \\ y_1 \end{bmatrix} \quad (2)$$

$$\begin{bmatrix} x'_1 \\ y'_1 \end{bmatrix} = \begin{bmatrix} a_0 \\ b_0 \end{bmatrix} + \begin{bmatrix} a_1 & b_1 \\ -b_1 & a_1 \end{bmatrix} \begin{bmatrix} x_1 \\ y_1 \end{bmatrix} \quad (3)$$

One pair of conjugate line segments would yield two constraints of the form in Equation 1. Using a given set of corresponding line segments, one can incorporate them in a least squares adjustment procedure to solve for the parameters of the registration transformation function (e.g., $a_0, b_0, a_1,$ and b_1 for 2D similarity transformation or $a_0, b_0, a_1, a_2, b_1,$ and b_2 for affine transformation).

Matching Strategy

After establishing the registration primitives, transformation function, and similarity measure, one should focus on how to establish the correspondence between conjugate primitives. Corresponding primitives in the reference and input images can be manually identified. However, the large amount of data and the need for fast registration methods mandate the automation of the process of identifying conjugate primitives. Therefore, a matching strategy has to be developed to manipulate the registration primitives, the transformation function, and the similarity measure to automatically establish the correspondence between conjugate primitives. In this research, the Modified Iterated Hough Transform (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 a 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 automatic relative orientation (Habib *et al.*, 2001a; Habib and Kelley 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 a subset of the involved parameters in the registration transformation function (depending on the number of the resulting constraints from a single matching hypothesis). The parameter solutions from all possible matching hypotheses are stored in an accumulator

array, which is a discrete tessellation of the range of expected numerical values for the parameters under consideration. Within the considered correspondences, correct matching hypotheses would produce the same parameters, which will manifest themselves 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 implementation of the MIHT strategy for automatic image registration can be summarized as follows:

- An accumulator array is formed for the parameters involved in the registration transformation function (e.g., 2D similarity or affine). The accumulator array is a discrete tessellation of the range of expected parameters solutions. The dimension of this array depends on the number of parameters to be simultaneously solved for, which is related to the number of entity pairings simultaneously considered as well as the number of constraints provided by a single matching hypothesis. In this research, the parameters are sequentially estimated one by one (i.e., we will be always dealing with a one-dimensional accumulator array).
- Approximations are assumed for the parameters which are not 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 from each matching hypothesis.
- After all possible matches have been considered; the peak in the accumulator array will indicate the correct solution of the parameter in question. Only one peak is expected for a given accumulator array (Figure 3).
- 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 (i.e., the estimated parameters do not significantly change from one iteration to the next).
- By tracking the hypothesized matches that contributed 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.

In addition to simultaneous estimation of the parameters of the registration transformation function and the correspondence between conjugate primitives, the MIHT strategy will help in verifying the validity of the selected transformation function between the reference and input images. The MIHT is expected to converge, if and only if, the registration transformation function is appropriate (assuming the existence of enough conjugate primitives in the involved datasets).

Experimental Results

Experiments have been conducted using real data from different imaging satellites to illustrate the feasibility and the robustness of the suggested registration process. The experiments incorporated a 1500 rows \times 1500 columns Landsat scene (15 m), 1500 rows \times 1500 columns SPOT scene (10 m), 1500 rows \times 1500 columns KOMPSAT scene (a Korean imaging satellite, 6 m resolution), and 6000 rows \times 6000 columns Ikonos stereo-pair (1 m), (refer to Figure 1 for sample patches). These scenes were captured at different times (multi-temporal) and exhibit significantly varying geometric and radiometric properties. First, the parameters of the registration transformation function (using 2D similarity and affine transformation functions) are estimated using thirty-six well-distributed tie points, which have been manually identified in the scenes (Table 1). The variance component ($\hat{\sigma}_v^2$) derived from the least squares procedure summarizes the quality of fit between the involved primitives in the registration process. Smaller variance component indicates a better fit between the registration primitives. The selection of common points in the various scenes proved to be a very difficult and time-consuming task. Analyzing the results in Table 1, one can see that the estimated variance component has improved using affine transformation when compared to that derived through 2D similarity transformation. Considering the estimated variance component resulting from the registration of the two Ikonos scenes using a 2D similarity transformation ($105.6437^{\wedge 2}$ pixel $^{\wedge 2}$), it can be concluded that such a transformation function is not a valid one. This can be attributed to the large scale associated with Ikonos scenes. However, using an affine transformation resulted in a much more reasonable variance component ($9.8179^{\wedge 2}$ pixel $^{\wedge 2}$), which signifies the validity of the affine transformation.

Afterwards, straight-line segments were manually digitized in the available scenes. As an example, Figure 4 shows the digitized segments in Ikonos and SPOT scenes. In this figure, one can see that there is no complete (i.e., one-to-one) correspondence between the digitized primitives in the input and reference images. The digitized segments are then incorporated in the MIHT strategy to automatically determine the correspondence between conjugate line segments as well as the parameters involved in the registration transformation function. The estimated registration transformation parameters as well as the corresponding variance component for all the datasets are listed in Table 2. Similar to the results from the point datasets, the affine transformation produced better results than the 2D similarity transformation. Moreover, comparing the results in Tables 1 and 2, one can see that utilizing linear features resulted in a better fit between the scenes than the solution derived using point features. This should be expected since identifying linear features in multi-resolution imagery is much more reliable and accurate than distinct points. Another observation from these results is the validity of the affine transformation as the registration transformation function relating the scenes under consideration.

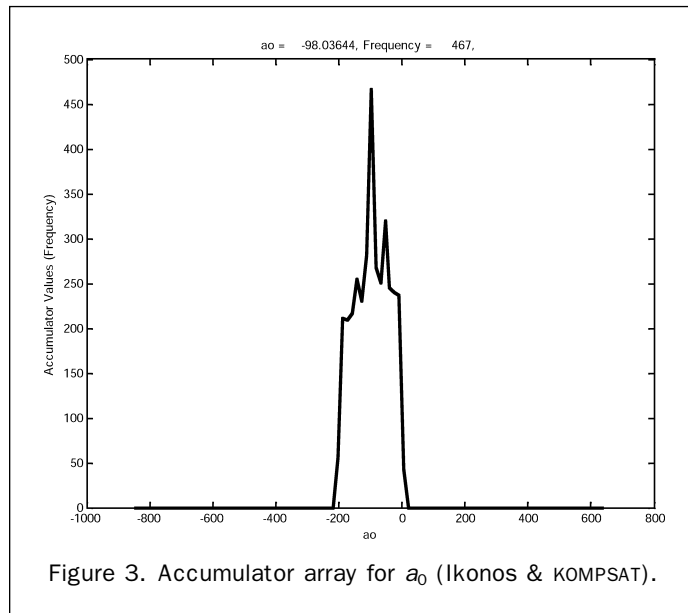


Figure 3. Accumulator array for a_0 (Ikonos & KOMPSAT).

TABLE 1. TRANSFORMATION PARAMETERS BASED ON MANUAL POINT MEASUREMENTS

2D-Similarity	Ikonos/Ikonos	Ikonos/KOMPSAT	Ikonos/SPOT	Ikonos/Landsat
$\hat{\sigma}_o^2$ (Pixel 2)	105.6437 $^{^2}$	4.6154 $^{^2}$	7.6691 $^{^2}$	7.4872 $^{^2}$
a_0 (Pixel)	56.81489	-99.65358	19.30487	0.13623
b_0 (Pixel)	-18.69259	-26.27758	-6.58108	-9.58130
a_1	1.029469	0.013085	0.08846	0.03292
b_1	0.071629	0.03187	-0.01589	-0.00472
Affine	Ikonos/Ikonos	Ikonos/KOMPSAT	Ikonos/SPOT	Ikonos/Landsat
$\hat{\sigma}_o^2$ (Pixel 2)	9.8179 $^{^2}$	2.2249 $^{^2}$	6.6021 $^{^2}$	6.5063 $^{^2}$
a_0 (pixel)	72.48928	-97.42270	-19.59451	0.04353
a_1	1.051263	0.12707	0.08756	0.03051
a_2	-0.001246	-0.03174	0.018210	0.00319
b_0 (pixel)	-2.419632	-25.58517	-6.49936	-9.85226
b_1	0.140353	0.03153	-0.01341	-0.00545
b_2	1.005484	0.13352	0.09020	0.03521

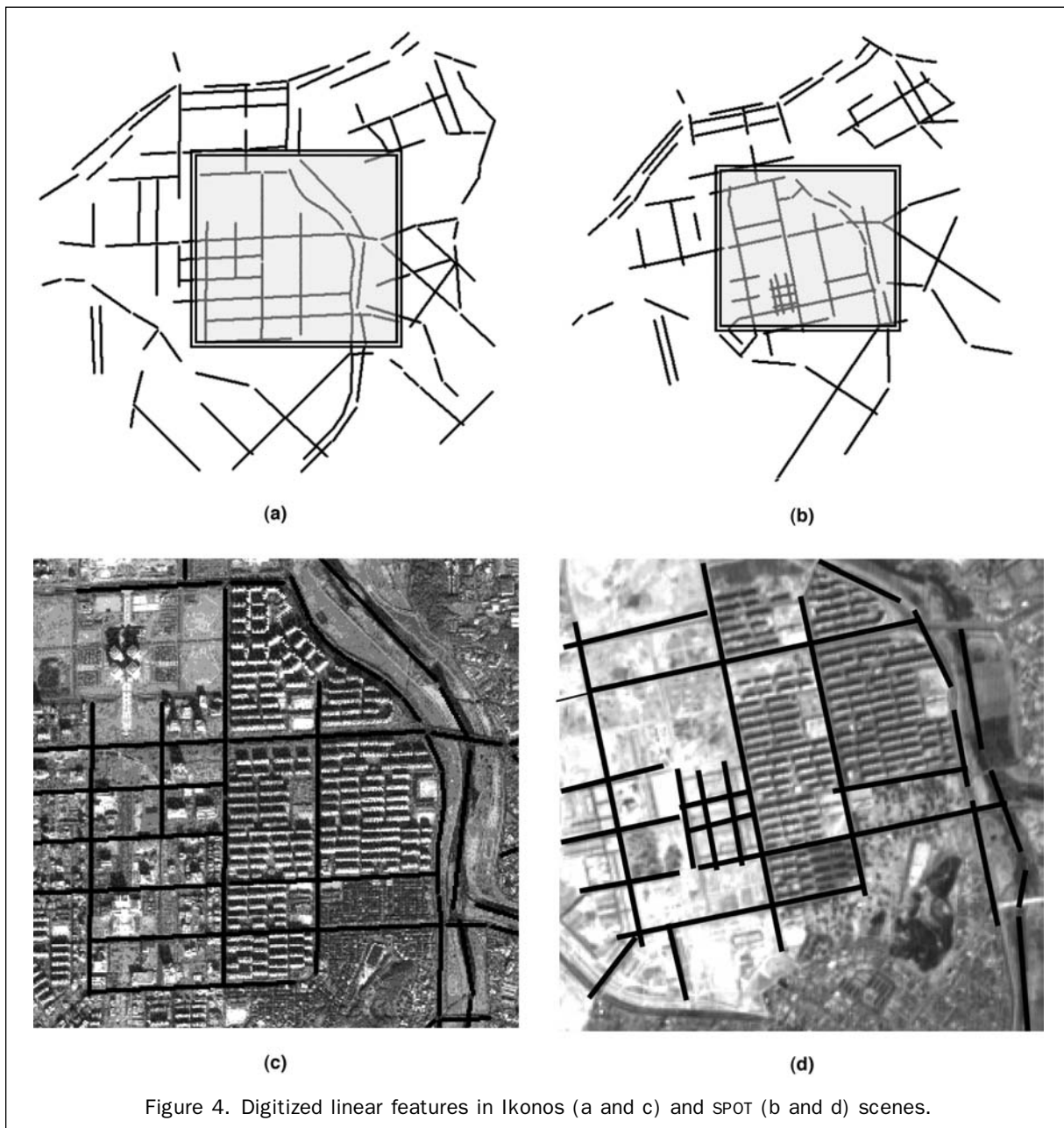


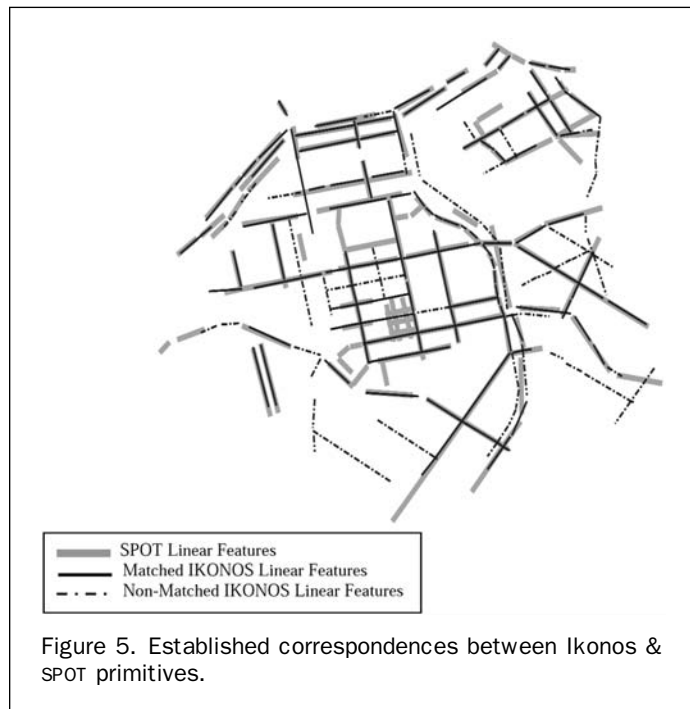
Figure 4. Digitized linear features in Ikonos (a and c) and SPOT (b and d) scenes.

TABLE 2. TRANSFORMATION PARAMETERS BASED ON AUTOMATICALLY MATCHED LINEAR FEATURES USING MIHT

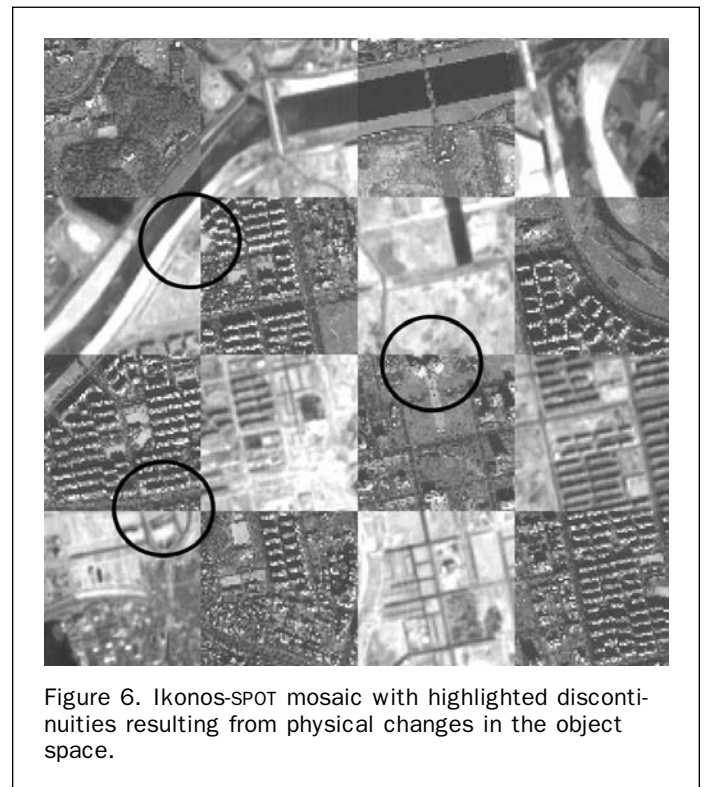
2D-Similarity	Ikonos/Ikonos	Ikonos/KOMPSAT	Ikonos/SPOT	Ikonos/Landsat
$\hat{\sigma}_o^2$ (Pixel ²)		4.243 ^{^2}	4.2587 ^{^2}	0.8947 ^{^2}
a_0 (pixel)		-103.94052	-19.69236	2.81575
b_0 (pixel)	No Conversion	-28.15586	-8.77077	-16.96265
a_1		0.13150	0.08704	0.02985
b_1		0.03197	-0.01583	-0.00435
Affine	Ikonos/Ikonos	Ikonos/KOMPSAT	Ikonos/SPOT	Ikonos/Landsat
$\hat{\sigma}_o^2$ (Pixel ²)	9.7022 ^{^2}	1.3567 ^{^2}	1.1634 ^{^2}	0.7193 ^{^2}
a_0 (pixel)	70.17578	-97.95137	-18.87100	2.20314
a_1	1.05151	0.12695	0.08738	0.02924
a_2	-0.00037	-0.03193	0.01905	0.00510
b_0 (pixel)	-22.33391	-27.23188	-8.24337	-16.94389
b_1	0.14591	0.03196	-0.01358	-0.003795
b_2	1.00904	0.13332	0.08881	0.029800

As mentioned before, the 2D similarity transformation does not constitute a proper registration transformation function between the Ikonos scenes. Therefore, as expected, the MIHT procedure did not converge for this dataset. As mentioned earlier, the affine transformation is valid when assuming relatively flat terrain. In this context, linear features are advantageous since they restrict the selected primitives along relatively flat terrain as represented by the road network. This might not be the case for point primitives that might have significant relief distortions (e.g., simultaneous considerations of points along the terrain as well as high rise buildings). Finally, observing the estimated shift components among the registered scenes (a_0 , b_0), one can see that the proposed strategy successfully converged without the need for approximate registration of these scenes.

Figure 5 depicts established correspondences between the digitized primitives in the Ikonos and SPOT scenes displayed in Figure 4. The estimated transformation parameters are used to resample the reference image to the coordinate



system associated with the input image. Figure 6 shows a mosaic image derived by combining Ikonos and SPOT scenes (where every other square patch in the reference image has been replaced by the corresponding resampled patch in the input image). It can be seen that features (e.g., roads, rivers, buildings) in the derived mosaic accurately fit each other (observe the smooth transition along the features within the resampled patches). This proves the validity of the estimated parameters of the transformation function relating these scenes. However, one can also note that there are some discontinuities along the boundaries between some of the resampled patches in Figure 6 (highlighted by circles). These discontinuities are attributed to physical changes in the object space between the epochs of capture of the involved scenes (the SPOT scene has been captured few years earlier than the Ikonos scene).



Conclusions and Recommendations for Future Research

With the flux of high-resolution imagery captured by space borne platforms (e.g., Landsat-7, Ikonos, Quickbird, Orbview, EROS-A1, KOMPSAT-I, and SPOT-5), there is an increasing need for a robust registration technique, which can tolerate varying geometric resolutions among the available scenes. This paper comprehensively addressed the key issues of an efficient semi-automatic registration methodology that can handle such scenes. First, straight-line segments have been chosen as the registration primitives. This selection is motivated by the fact that they can be reliably identified when considering multi-resolution scenes. Then, the registration transformation function is analyzed to determine the mathematical relationship between conjugate primitives in the scenes to be registered. It has been established that affine transformation can be used as the registration transformation function for scenes captured by satellite imaging systems with narrow angular field of view. Moreover, 2D similarity transformation can be used as another alternative for some applications with less demanding accuracy requirements. Afterwards, the geometric attributes of conjugate primitives are manipulated to derive a similarity measure describing the necessary constraints for the coincidence of these primitives after establishing the registration procedure. It is important to note that the similarity measure has been developed while considering the fact that the end points of conjugate line segments are not identical. Finally, the registration primitives, transformation function, and similarity measure have been used in a matching strategy based on MIHT to automatically and simultaneously establish the correspondence between conjugate primitives as well as the parameters of the transformation function. Experimental results showed the feasibility and the robustness of the suggested approach that could tolerate possible discrepancies between the imagery due to varying sensor operational principles, as well as, changes in the object space without the need for approximate registration of the involved imagery. Moreover, the results proved the superiority of straight-line segments over distinct points. This should be expected since linear features can be identified more accurately than distinct points. In addition, the results verified the fact that affine transformation yields better registration when compared with 2D similarity transformation.

It should be noted that the proposed technique could be used to robustly and simultaneously estimate the parameters of the registration transformation function, as well as, the feature-to-feature correspondence between multi-temporal, multi-resolution, and multi-source satellite imagery. Moreover, the methodology can be expanded to allow for change detection and updating purposes. Current research is focusing on automatic extraction of the registration primitives from the input imagery, as well as the utilization of free-form linear features, represented as a sequence of straight line segments (polylines). In addition, further investigation will be conducted to evaluate the limits for the validity of the affine transformation as the registration transformation function. Finally, the proposed strategy will be used to establish the registration of satellite scenes with vector data in existing GIS databases for change detection and updating applications.

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