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Survey of image registration methods

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3.1 Introduction

Automatic image registration, bringing two images into alignment by computing a moderately small set of transformation parameters, might seem a well-defined, limited problem that should have a clear, universal solution. Unfortunately, this is far from the state of the art. With a wide spectrum of applications to diverse categories of data, image registration has evolved into a complex and challenging problem that admits many solution strategies. The growing availability of digital imagery in remote sensing, medicine, and numerous other areas has driven a substantial increase in research in image registration over the past 20 years. This growth in research stems from both this increasing diversity in image sources, as image registration is applied to new instruments like hyperspectral sensors in remote sensing and medical imaging scanners in medicine, and new algorithmic principles, as researchers have applied techniques such as wavelet-based features, information theoretic metrics and stochastic numeric optimization.

This chapter surveys the diversity of image registration strategies applied to remote sensing. The objectives of the survey are to explain basic concepts used in the literature, review selected algorithms, give an overall framework to categorize and compare algorithms, and point the reader to the literature for more detailed explanations. While manual and semi-manual approaches are still important in remote sensing, our primary intent is to review research approaches for building fully automatic and operational registration systems. Following the survey article by Brown (1992), we review an algorithm by considering the basic principles from which it is constructed. These principles include, among others, the measure of similarity used to compare images and the optimization algorithm used to optimize the measure. Most image registration algorithms in the literature and those used in practice are based on variations on these basic elements and their combination. Indeed, a reader familiar with the basic, major principles and their various combinations, can easily gain a good understanding of a new image registration technique

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or system. A survey of the scientific literature on image registration specifically for remote sensing is provided by Fonseca and Manjunath (1996). Previous surveys of the general image registration literature include Brown (1992) and Zitová and Flusser (2003), while general books on registration include Modersitzki (2004) and Goshtasby (2005). Surveys limited to medical applications, with specific focus on mutual information, include Maintz and Viergever (1998) and Pluim *et al.* (2003).

Within the wide spectrum of image registration principles and applications, this chapter focuses on techniques relevant to automatic registration of regular two-dimensional image data from Earth satellite instruments used for remote sensing, primarily those instruments sensing in the visible or near-visible spectra. We do not treat extensively methods for instruments that use radar, those that directly produce range information, or sensors borne aloft by airplanes and balloons. These forms of imagery may differ from satellite imagery in perspective and other characteristics. However, since new image registration techniques are often imported into remote sensing from research undertaken in other fields, we also review some methods from those fields as appropriate. Other fields with active research in image registration include medical imaging, video analysis for multimedia, and robotics. These fields differ from remote sensing in their requirements for image registration. In contrast to remote sensing, medical image registration works with a large number of imaging modalities from whole body to retinal scans, and involves tissues that can deform or change drastically. Similarly, image registration for multimedia video analysis and robotics works on short-range imagery of complex 3D scenes, rather than long-range imagery of planetary surfaces. We specifically do not include in our review articles on elastic or nonrigid registration, 3D volumetric registration, and 3D range registration. Readers interested in the latter topics are referred to Maintz and Viergever (1998), Lester and Arridge (1999), Goshtasby (2005), and Salvi *et al*. (2006).

Regardless of the field of application, the articles reviewed in this chapter originate roughly from three overlapping communities. The image processing community focuses on developing methodologies and techniques, and a research contribution presents usually a novel technique or an evaluation method. Such contributions include mostly proof-of-concept demonstrations on limited image sets so the techniques described can be considered promising prototypes. A second set of contributions comes from the community of ground support satellite teams. This community specializes in the design of effective, practical algorithms used to create orthorectified image products for a limited set of instruments. The techniques they describe serve as a basis for successful operational systems run on extensive datasets. Operational satellite teams have an end-to-end understanding of data processing used in their satellite system, with inside knowledge of sensor and satellite engineering. They use image registration to update orbital and navigational

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models, calibrate sensors, and validate image products. Given the initial satellite position and orientation, their imagery may be closely aligned prior to registration, which reduces the search time during registration. The last set of contributions is made by the remote sensing user community. The articles by this community raise various issues and describe common practice of using image registration in the analysis of imagery for specific applications, such as land use planning or crop yield forecasting. The remote sensing user community has a broad set of interests, including determining the best algorithm to use for remotely sensed datasets, the extent to which misregistration errors impact their analyses, whether their data have been registered properly, and which algorithm best combines heterogeneous satellite image sources with maps, Geographic Information Systems (GIS), airborne instrument imagery, and field data. End user datasets may vary greatly in initial alignment, so fully automatic registration software would need to be more robust to large geometric transformations. In Eastman *et al*. (2007) we briefly surveyed current practice by the operational and user communities, and noted the different requirements for them.

Each article on image registration addresses some variation of the general problem. The variation addressed may vary by community or application, or the research intentions of the authors. An overriding objective is to develop an accurate, fully automatic registration algorithm that is successful without human intervention. Other objectives an article may address include:

(1) Improving robustness and reliability, so a registration algorithm better handles noise, occlusions, and other problems.
(2) Refining the geometric transformation to better model the complex physical imaging process of an instrument and satellite.
(3) Increasing the subpixel accuracy of the transformation computed to meet higher operational requirements.
(4) Speeding up the registration process to handle greater throughput and more complex algorithms.
(5) Handling large and unknown initial transformation estimates, so an algorithm can match across greater displacements.
(6) Managing multimodal registration, so an algorithm can be applicable to images with radiometric, scale, and other differences that might be present across band, instrument, or platform.

As the topic of image registration for remote sensing is broad and can be broken down into many different categorical schemes, this chapter addresses each subtopic from different aspects. In Section 3.2 we define a terminology for the components of image registration. This terminology will allow us to decompose systems into their major components. In Section 3.3 we review major algorithmic categories to

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examine how these various components are most commonly combined into full systems. In Section 3.4 and Section 3.5 we review, respectively, particular characteristics of geometric and radiometric transformations relevant to remote sensing. In Section 3.6 we review articles that evaluate image registration algorithms and systems. Finally, Section 3.6 contains concluding remarks.

3.2 Elements of image registration algorithms

An instance of a pairwise image registration problem is to align one image, the *sensed image*, onto a second image, the *reference image*, by computing a transformation that is optimal in some sense. We will define an image registration problem by the following five elements:

(1) Reference image, $I_1\ (x, y)$, that is generally taken to be unchanged.
(2) Sensed image, $I_2\ (x, y)$, that is transformed to match the reference.
(3) Geometric transformation, f, that maps spatial positions in one image to the other.
(4) Radiometric transformation, g, that transforms intensity values in one image to the other.
(5) Noise term, $n\ (x, y)$, that models sensor and other imaging noise.

These definitions lead to the following relationship between the reference and sensed images, where (x, y) represent the coordinate system in the reference image, and (u, v) the coordinate system in the sensed image. Two image locations in the reference and sensed image are said to correspond or to be corresponding points if they are mapped into each other under the geometric transformation, i.e.,

$$I_1(x, y) = g(I_2(f_x(u, v), f_y(u, v))) + n(x, y). \tag{3.1}$$

The above informal model is only intended to provide context for our review. Readers interested in a formal mathematical definition of the image registration problem are referred to Modersitzki (2004).

Intuitively, solving an instance of the image registration problem requires computing the geometric and radiometric transformations, so that Eq. (3.1) holds. More generally, the image registration problem is to devise an algorithm that, for all pairs of images from two sets of images in the domain of interest, will compute the optimal transformations for any instance, where the definition of optimal depends on the choice of similarity measure as defined below.

This simplified, general model has three immediate caveats. Requiring strict equality between corresponding image intensities in the reference and sensed images is a strong constraint. This constraint is frequently relaxed to a statistical relationship (Roche *et al.*, 2000) or an information-theoretic one (Maes *et al.*, 1999), which require that corresponding regions show similar distributions under

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the optimal transformations. Also, the noise term can confound a number of factors, both additive and multiplicative, so a single additive term is only a weak approximation. Some image differences can be the result of atmospheric or sensor noise, while others could stem from temporal ground changes that are the signal of interest. Thus, care must be used in defining image differences as "noise."

From the general model relating the reference and sensed image, we may categorize algorithms according to the widely accepted framework given in Brown (1992). Brown's review described four standard elements in the design of an image registration algorithm:

(1) Search space that defines the possible transformations between the reference and target images, both geometric and radiometric, that will be considered.
(2) Feature space of information content extracted from the images to be used in their comparison.
(3) Similarity metric that defines the merit of matching image features under given transformations.
(4) Search strategy used to find the optimal transformation, i.e., the transformation in the parameter space that maximizes the similarity metric.

Beyond these four standard elements of an image registration scheme, there is a fifth element critical to their understanding, namely the validation of an image registration algorithm as accurate and reliable. While not an integral component of the registration scheme itself, the procedures of testing, evaluating and validating these schemes comprise an important element in studying various approaches of image registration.

3.3 General approaches to registration

Image registration algorithms are often characterized as *area-based* or *feature-based*. In area-based algorithms, areas or regions of the original image data are matched with minimal preprocessing or with preprocessing that preserves most of the image data. These algorithms may compute the differences of raw image pixel values, or use all pixel values to compute an intermediate full-information representation like the Fourier coefficients. Area-based methods are often labeled correspondence-less matching, as an entire area is matched without constructing an explicit correspondence between points in the two images. In feature-based algorithms, on the other hand, the original images are preprocessed to extract distinctive, highly informative features that are used for matching. These algorithms may extract a few distinctive control points (CPs), or detect dense edges/contour maps for matching. Image registration systems for remote sensing often combine the two approaches at different levels. At one stage the system may use

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feature-based control points, followed at a later stage by area-based matching. This may be very appropriate when large distortions or displacements make feature-point matching more robust. This is because local regions are warped, so individual pixels align very poorly, but derived features are more invariant to the distortions. After those large transformations are initially accounted for, area-based matching can be effectively performed.

3.3.1 Manual registration

While laborious and prone to error, manual registration, which is based on selection of control points, is still widely used and highly regarded in the remote sensing community. The user visually selects distinctive matching points from two images to be registered, and then uses those points to compute and validate a geometric transformation. Remote sensing software packages, such as ITT's ENVI and PCI Geomatics' Geomatica, typically support manual selection. One advantage to manual registration is that it is easy to understand and implement. Manual selection allows the user to refine the set of control points for a number of reasons, including focusing on a region of interest while ignoring sections of the image that are not under study, fine-tuning the geometric transformation to meet accuracy objectives, and basing the control points on known ground features. And, while some imagery can be difficult for manual control point selection, in general, users can adapt to more data sources than a typical algorithm. In some cases, considerable effort and care goes into the selection of ground control points. Researchers may visit a study site to select and label with Global Positioning System (GPS) coordinates a set of robust ground features like road intersections (Wang and Ellis, 2005b). These georeferenced control points are then located in the imagery and integrated into an image-to-image registration scheme. Manually selected control points have been used to initialize automatic matching steps (Kennedy and Cohen, 2003) and are often used for accuracy studies on automatic systems. The research emphasis with manual registration is typically on the quality of the final geometric transformation, as the software systems support complex empirical and physical models such as rational polynomials. In addition to manual selection of control points, remote sensing software packages usually support the automatic selection and correlation-based registration of control points, although they vary in the nature and extent of the automatic selection.

3.3.2 Correlation-related methods

Correlation-related methods directly compute a similarity measure for corresponding image regions by pixelwise comparisons of intensity values. Often called

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template matching, a region from one image is translated around the other to find the alignment that optimizes the similarity measure. The similarity measure for the absolute difference of pixel intensities is given by

$$D[\Delta x, \Delta y] = \sum_x \sum_y |I_1(x, y) - I_2(x + \Delta x, y + \Delta y)|, \tag{3.2}$$

where Δx, Δy denote, respectively, the horizontal and vertical shifts in the sensed image, and the summation is carried out over all x, y locations of an image region. The above similarity measure, expressed by the L_1-norm as the sum of absolute differences, can be expressed alternatively in terms of the L_2-norm as the sum of squared differences. The correlation coefficient itself sums the product of intensity values, in essence maximizing an inner product. The naive brute-force search approach is to evaluate these similarity measures according to Eq. (3.2), that is, by summing over all x, y in the region, and letting Δx, Δy vary over a predefined search window until finding the optimal translations. Although correlation-related methods are fundamental to image registration, they have a number of drawbacks that need to be addressed for practical applications.

First, the brute-force approach is computationally expensive. Specifically, it requires $O(n^2m^2)$ operations, where n and m denote, respectively, the dimension of the image region and search window. Although this may be acceptable for limited size regions and search windows, faster methods should be used, in general. Indeed, there are a number of methods for speeding up the calculation of the above correlation measures. A fast computation of the correlation coefficient in the frequency domain deserves special consideration. See Subsection 3.3.3 below. Other approaches include partial computations, coarse-to-fine pyramid search, specialized parallel hardware, and numerical optimization.

For partial computation, the full similarity measure is not computed for all locations in the search window. Instead, it is computed at sampled locations in the search window (Althof *et al*., 1997). Alternatively, the computation can be truncated if it exceeds a certain threshold or a previously computed minimum. The *sequential similarity detection algorithm* (SSDA) accumulates the sum of absolute differences until the measure becomes too large for the current alignment to provide the likely minimum (Barnea and Silverman, 1972). Huseby *et al*. (2005) used the SSDA method to register Advanced Very High Resolution Radiometer (AVHRR) and Moderate Resolution Imaging Spectraradiometer (MODIS) data. Another method, which projects a 2D region into two 1D correlations, lowers the computational cost and adds a noise-smoothing effect (Cain *et al*., 2001). The 2D to 1D projection is handled as follows. The columns and of the subimage being matched are summed to produce a vertical, 1D array. Similarly, the rows are summed to produce a horizontal, 1D array.

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For coarse-to-fine pyramid search, the image is blurred and decimated into a sequence of smaller, lower-resolution images of sizes that are a decreasing sequence, typically of powers of two. Translations in a given image are clearly reduced in the smaller images, so the search window for these images becomes smaller accordingly. Once a solution is found for a smaller image, the resulting alignment is extrapolated to the next higher-resolution image. The search result is refined repeatedly in this fashion through the highest-resolution image. Coarse-to-fine search has the added advantage that the blurring and decimation can smoothen the objective function (i.e., the similarity measure), thereby reducing the impact of local minima and noise.

Regarding specialized hardware, the inherent parallel nature of the problem can be exploited to parallelize the correlation computation by using parallel processing units (Le Moigne *et al*., 2002), *application specific integrated circuits* (ASICs) (Gupta, 2007), *field-programmable gate arrays* (FPGAs) (Sen *et al*., 2008), or *general purpose graphics processing units* (GPUs) in graphics cards (Köhn *et al*., 2006).

Finally, another alternative to brute-force search is a variant of gradient descent numerical optimization. In this approach the L_2-norm similarity measure is computed by an iterative solution to a least-squares formulation (Dewdney, 1978; Lucas and Kanade, 1981; Irani and Peleg, 1991; Thévenaz *et al*., 1998; Irani and Anandan, 1999; Baker and Matthews, 2001). Assuming that the similarity measure is smooth without local minima, the iterative process will converge to the minimum cost alignment in $O(n^2)$ time (Dewdney, 1978).

The brute-force approach becomes more expensive when used for subpixel accuracy, as the use of fractional pixel increments increases the computational cost over integral increments. The previously mentioned gradient descent approach can address this, as the iterative process naturally converges to subpixel accuracy (Irani and Peleg, 1991; Baker and Matthews, 2001). An alternative approach is to compute the similarity measure at integral displacements, and then use polynomials computed over a local neighborhood to interpolate a subpixel optimum (Lee *et al*., 2004). Even when interpolated over small 3×3 neighborhoods, the latter can be effective to a tenth of a pixel.

The computational cost of the brute-force approach can be even more significant with a complex geometric transformation beyond translation. The addition of each parameter, due to rotation, scale, skew, and high-order distortions, multiplies the size of the search space. In practice, correlation is often used on small image regions or chips, where translation is an adequate approximation, even if the entire image is to be registered by a complex physical model (Theiler *et al*., 2002). When more complex models are required, albeit still relatively low order, such as rotation, scale, and translation (RST), affine, or homography, the extra parameters can be

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incorporated into the least-squares formulation by a linearized approximation (Irani and Peleg, 1991; Thévenaz *et al*., 1998).

The basic correlation similarity measures can be weakened by noise, occlusions, temporal changes, radiometric differences in multimodal imagery, and other sources that may influence pixel differences. This is a major reason for the development of more statistically complex similarity measures, or feature-based methods, as discussed later in this section.

Still, correlation measures themselves can be made more robust and more adapted to complex imagery. Images can be preprocessed to enhance image frequencies less susceptible to noise sources, either by similar smoothing due to the coarse-to-fine projection approaches mentioned previously, or by edge enhancement (Andrus *et al*., 1975). Keller and Averbuch (2006) presented an *implicit similarity* measure, which treats the two images asymmetrically by computing the gradient magnitude in one image, and edges in the other. For any displacement, the measure is computed by summing the gradient magnitude covered by edges in the second image. Kaneko *et al*. (2003) dealt with occlusion by selective masking. Robust statistical measures, such as M-estimators, can be used to reduce the influence of outlying noise values. Arya *et al*. (2007) presented a version of normalized correlation, based on M-estimators, which is robust to occlusions and noise. Kim and Fessler (2004) used M-estimators in intensity correlation for a medical application, and demonstrated better performance than that obtained by using the *mutual information* (MI) measure. Radiometric differences between images can also be handled by a gradient descent approach to the least-squares formulation, provided that they can be modeled by a small set of parameters. Examples include affine radiometric transforms (Gruen, 1985) and gamma correction (Thévenaz *et al*., 1998). Georgescu and Meer (2004) integrated radiometric correction with robust M-estimators in a gradient descent approach. Statistical alternatives to basic correlation are the correlation ratio and the Woods measure (Roche *et al*., 2000).

While the deficiencies of correlation methods are often cited in papers on new registration techniques, the approach is important and remains widely used in remote sensing applications (Emery *et al*., 2003; Lee *et al*., 2004). In Eastman *et al*. (2007) we reviewed several image registration schemes in major satellite ground systems, six of which used area-based correlation. These schemes are presented in Table 3.1 and described below. All the operational systems were developed by ground support teams, and they share a number of characteristics beyond the use of normalized intensity correlation. They all perform matching in local regions (rather than global matching), deal only with translation (since it dominates in small regions), and use preconstructed databases of carefully selected image regions, topographic relief correction of features before correlation, and cloud masking or thresholds to eliminate cloudy regions. Most systems use subpixel

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Table 3.1 *Operational image registration systems based on correlation*

Instrument	Satellite	Resolution	Similarity
ASTER	Terra	15–90 m	Correlation to DEM corrected CPs
MISR	Terra	275 m	Correlation to DEM corrected CPs
MODIS	Terra	250 m–1 km	Correlation to DEM corrected CPs
HRS	SPOT	2.5 m	Correlation to DEM corrected data
ETM+	Landsat-7	15–60 m	Correlation to arid region CPs
VEGETATION	SPOT	1 km	Correlation to DEM corrected CPs

estimation but vary in how the subpixel transformation components are computed. Also, operational groups report the following practical registration issues that need to be addressed: effectiveness of normalized correlation in cross-band registration, adaption to thermal changes in satellite geometry and minor problems in orbit data, inadequate uniform sampling of CPs across the image, and suitability of a specific ground location for correlation for different reasons. A ground location can be unsuitable for correlation because the ground features are uniform and indistinct, because seasonal changes in temperature and vegetation cause the imagery to significantly vary, or because human activity causes the imagery to vary.

Iwasaki and Fujisada (2005) described the image registration system for the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), a 14-band multispectral imager launched in 1999 on the Terra (EOS-AM1) satellite. Registration was done to a database of about 300–600 CPs which were mapped onto topographic maps. The similarity measure used was normalized correlation with transformation limited to translation. Matches were rejected for correlation less than 0.7 or if clouds were detected. Subpixel estimation was calculated by fitting a second-order polynomial to the correlation values. In a retrospective study the authors cited accuracies of 50 m, 0.2 pixels and 0.1 pixels, respectively, for three bands of different resolution. Jovanovic *et al*. (2002) described the geometric correction system for the Multiangle Imaging SpectroRadiometer (MISR) instrument on the Terra satellite. Registration was conducted on a database of 120 ground control points (GCPs) represented by nine 64×64 image chips from Landsat Thematic Mapper (TM) images, one chip from each spectral band. Each control CP was of an identifiable ground feature that could be located to 30 m, and was selected for seasonally invariant features. The chips were mapped onto terrain-corrected imagery and a ray-casting algorithm was used to warp each chip to the appropriate geometry for the appropriate MISR camera. Chip matching was done to subpixel accuracy for translation, potentially to $1/8$ of a pixel, using least-squares optimization (Ackerman, 1984).

Wolfe *et al*. (2002) described a geolocaton system (see also Xiong *et al*., 2005) for the MODIS instrument on the Terra satellite. Registration was carried out on a database of 605 land CPs known to 15 m in 3D. For each CP, 24-km^2 chips (of 30-m/pixel resolution) were constructed from Landsat TM bands 3 and 4 over cloud-free areas, predominantly along coastlines and waterways. Higher-resolution TM chips were resampled to MODIS resolution, using the MODIS point spread function and nominal MODIS position information. A fractional sampling interval was used to get subpixel accuracy with a threshold of 0.6 for rejection.

Baillarin *et al*. (2005) described the automatic orthoimage production system, ANDORRE, with its algorithmic core TARIFA (French acronym for Automatic Image Rectification and Fusion Processing) for the SPOT-5 High Resolution Stereoscopic (HRS) instrument, launched in 2002. (The French satellite SPOT stands for Earth observation satellite.) ANDORRE uses an extensive database of orthoimagery tiles integrated with Digital Elevation Model (DEM) data to generate, via ray tracing, a simulated image for matching. Matching is done using multiresolution search with the number of levels set to keep a 5×5 pixel size search window. CPs are automatically found, matched by correlation, and used to calibrate a parametric model. Geometric outliers and CPs with correlation coefficient below 0.80 are rejected.

Lee *et al*. (2004) described image registration for the geolocation of ETM+, an instrument on the Landsat-7 satellite that was launched in 1999. ETM+ specifications include locating an image pixel to 250-m absolute geodetic accuracy (namely, each pixel is off by at most 250 m from its true ground position), 0.28 pixels band-to-band (that is, bands have a relative misregistration of less than a $1/3$ of a pixel at most), and 0.4 pixels temporal registration (i.e., images taken of the same area over time have less than $1/2$ pixel misregistration). These three requirements lead to multiple registration approaches for calibration and assessment. Geodetic accuracy is updated by correlating systematically corrected panchromatic band regions against a database of CP image chips extracted from USGS digital orthophotos. A second correlation algorithm evaluates band-to-band alignment by subpixel registration with second-order fit to the correlation surface.

Sylvander *et al*. (2000) described the geolocation system for the VEGETATION instrument on the SPOT satellites, which became operational since the launch of SPOT-4 in 1999. A database of approximately 3500 CPs was built from VEGETATION images. Each distinct ground CP location was represented in the database as four image chips taken from images of different seasons and orientations. Correlation-based matching was done under the control of human operators who ensure that there are ten matched points per orbit to compute satellite position corrections. Multispectral registration to subpixel accuracy of 0.11 pixels was reported.

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3.3.3 Fourier-domain and other transform-based methods

Frequency domain methods provide primarily a fast alternative for computing the correlation coefficient similarity measure. A frequency transform converts a digital signal, or an image, to a collection of frequency coefficients that represent the strength of each frequency in the original signal. For example, if the original image has a large number of ridges, then the frequency domain will have large coefficients related to the regular distance between the ridges. Transform-based registration methods are based on the premise that the information in the transformed image will make the geometric transformation easier to recover.

Fourier domain methods are based on Fourier's *shift theorem*, which states that if $g(x, y)$ is a translated version of a signal $f(x, y)$ in the spatial xy domain, then the corresponding Fourier transforms $G(u, v)$ and $F(u, v)$ in the frequency uv domain are related by a phase shift that can be recovered efficiently. For image registration, the two images are transformed to the frequency domain by the *fast Fourier transform* (FFT). These transforms are then multiplied efficiently in the frequency domain, and their product is transformed back (via the inverse FFT) to the spatial domain for recovery of the translation. (The desired translation is found at the location of the inverse transform peak.) While the computation itself is equivalent to that of the correlation coefficient in the spatial domain, the computational cost of the above method is $O((n + \mathrm{m})^2 \log(n + m))$, rather than the brute-force $O(n^2m^2)$ (Dewdney, 1978).

Notwithstanding the relative computational efficiency of standard Fourier-based methods, in comparison to the brute-force computation of the correlation coefficient in the spatial domain, the two approaches share many drawbacks in terms of handling subpixel displacements, geometric transformations beyond translation, and sensitivity to noise. Also, it would be difficult for the Fourier approach to recover large displacements. Thanks to various modifications, however, Fourier-based registration in the frequency domain can be adapted to handle these problems. De Castro and Morandi (1987) extended the method to rotation, while Chen *et al*. (1994) and Reddy and Chatterji (1996) extended it to transformations that consist of rotation and scale, as well as translation. Specifically, Chen *et al*. (1994) combined the shift-invariant Fourier transform and the scale-invariant Mellin transform, leading to the term "Fourier-Mellin transform." Their method is also known in the literature as *symmetric phase-only matched filtering* (SPOMF). Abdelfattah and Nicolas (2005) applied the invariant Fourier-Mellin transform to register Interferometric Synthetic Aperture Radar (In-SAR) images, and demonstrated an improved signal-to-noise ratio (SNR) over standard correlation. Keller *et al*. (2005) used the pseudopolar Fourier transform for computing rotation in a more robust and efficient manner.

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Shekarforoush *et al*. (1996) extended the method to subpixel displacements. This was further refined by Stone, Orchard, Chang and Martucci (2001) and Foroosh, Zerubia and Berthod (2002) who demonstrated effective registration across spectral bands in SPOT satellite imagery. The high accuracy required of subpixel extensions emphasizes aliasing artifacts from rotation effects at image boundaries. These effects, which come from interpolation of rotated images, were addressed by Stone *et al*. (2003). The same authors also addressed the integration of cloud masks into Fourier methods in McGuire and Stone (2000). Zokai and Wolberg (2005) adapted the method to large displacements with perspective distortions. Orchard (2007) also addressed the recovery of large displacements and rotations, integrating the Fourier transform into a gradient descent framework for an exhaustive global search, while demonstrating robustness to multimodal radiometric differences in remote sensing and medical imagery. An additional Fourier-based method is due to Leprince *et al*. (2007), who combined a Fourier method on local image regions with a global model of the imaging systems to achieve subpixel registration within $1/50$ of a pixel.

The Fourier basis functions have infinite support and they do not spatially localize the frequency response. On the other hand, wavelet basis functions, such as the Haar, Gabor, Daubechies, finite Walsh and Simoncelli wavelets used in image registration (Li *et al*., 1995; Hsieh *et al*., 1997; Le Moigne *et al*., 2000; Zavorin and Le Moigne, 2005; Lazaridis and Petrou, 2006), do have finite support and thus do localize the frequency response of an image feature. A Fourier coefficient represents a particular frequency but does not indicate where in the image features with that frequency occurred. Wavelet features, on the other hand, give both frequency and position information. As a result, wavelets are not used in the same way as Fourier coefficients. Rather than apply the shift theorem (as in the Fourier case), wavelets are used to decompose the image into higher-frequency, edge-like features, and lower-frequency features. The higher-frequency features are used typically as dense edge features for correlation- or feature-based matching. This will be further discussed in Subsection 3.3.5.

3.3.4 Mutual information and distribution-based approaches

Requiring equality between image intensities is a strong constraint, which is not valid in many cases. For cross-band and cross-instrument fusion, the image intensities may be related by nonmonotonic or even nonfunctional relationships, requiring powerful similarity measures for effective matching that are based on statistical relationships. In this case, the similarity measure is based on comparing local intensity distributions rather than individual pixel values.

The most effective of these measures has proven to be the *mutual information* (MI) measure and its variants. MI-based registration was first introduced in the

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medical imaging domain by Maes *et al*. (1997) and Viola and Wells (1997). See also Pluim *et al*. (2000), Thévenaz and Unser (2000) and the review of MI-based methods in medical imaging (Pluim *et al.*, 2003). These methods make very weak assumptions about the relationship between pixel intensities in the two images, and they do not require a monotonic or any functional model. Mutual information is an information-theoretic quantity that measures the spread of the values in a joint histogram represented by a 2D matrix. If two images match perfectly, then the joint histogram of their intensities should cluster around the diagonal of the matrix; otherwise, the values spread off the diagonal. Denoting the image intensities by the random variables X and Y, the mutual information measure is defined by

$$MI(X;Y) = \sum_{x \epsilon X} \sum_{y \epsilon Y} p_{X,Y}(x, y) \log \left(\frac{p_{X,Y}(x, y)}{p_X(x)\, p_Y(y)} \right), \tag{3.3}$$

where $p_X(x)$ and $p_Y(y)$ denote, respectively, the probability density function (PDF) of X and Y, and $p_{X,Y}(x, y)$ denotes the joint PDF of X and Y.

A number of authors have addressed various issues, such as efficiency, accuracy, and robustness, regarding the application of MI in image registration. Maes *et al*. (1999) looked at ways of obtaining efficient speedups, by investigating a multiresolution pyramid approach in combination with several (non)gradient-based optimization algorithms. Shams *et al*. (2007) applied MI to gradient values to compute more efficiently an initial scale and translation estimate before refining the registration by a variation of Powell's numeric optimization. The MI measure is subject to scalloping artifacts that stem from interpolation errors that introduce false local optima. The scalloping artifacts show up as ridges in the similarity measure surface. A number of authors have considered refinements to improve the computation of the joint histogram. See, for example, Chen *et al*. (2003), Dowson and Bowden (2006), Ceccarelli *et al*. (2008), Dowson *et al*. (2008), and Rajwade *et al*. (2009). Other authors have looked at improving, generalizing, and unifying MI with other information-theoretic measures. See Bardera *et al*. (2004), Pluim *et al*. (2004), and Knops *et al*. (2006).

Despite its wide use in medical imaging and good potential for multimodal fusion, MI-based methods have yet to be used extensively in remote sensing applications. Still, research-oriented articles have demonstrated promising approaches on limited image sets. Kern and Pattichis (2007) gave a thorough review of MI implementation details, and developed a gradient descent version that was extensively tested on synthetically generated, cross-band image pairs acquired by the Multispectral Thermal Imager (MTI) satellite. Cole-Rhodes *et al*. (2003) integrated MI with a wavelet pyramid, and used a stochastic gradient numeric optimization search approach to register multimodal, multiscale imagery acuired by IKONOS,

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Landsat ETM, MODIS, and Sea-viewing Wide Field-of-view Sensor (SeaWiFS). Chen *et al*. (2003) applied MI with different interpolations (nearest neighbor, linear, cubic, and partial volume) to register Landsat TM, Indian Remote Sensing Satellite (IRS), Panchromatic (PAN), and Radarsat Synthetic Aperture Radar (Radarsat/SAR) images over the San Francisco Bay Area, California. (Partial volume interpolation was found to be most effective.) In similar tests, Chen *et al*. (2003) used Landsat TM imagery to establish the ability of generalized partial volume algorithms to reduce interpolation artifacts in the similarity measure. Inglada and Giros (2004) systematically investigated the application of different similarity measures to multisensor satellite registration of SPOT and ERS-2 data, including correlation, correlation ratio, normalized standard deviation, MI and the related Kolmogorov measure. Cariou and Chehdi (2008) used MI with gradient descent to register airborne pushbroom sensor data to a reference orthoimage, computing a geometric transformation based on explicit airplane orientation parameters. A recent report (Nies *et al*., 2008) has discussed the application of MI to the rather noisy SAR imagery. He *et al*. (2003) applied a generalization of MI, the Jensen-Rènyi divergence measure, to the registration of airplane profiles in Inverse Synthetic Aperture Radar (ISAR) images.

3.3.5 Feature point methods

A feature-point registration algorithm first extracts a set of distinctive, highly informative feature points from both images, and then matches them based on local image properties. Feature points are referred to by different names in the literature, including control points, ground control points, tie-points, and landmarks. Care must be taken, though, with respect to the terminology used in a paper to distinguish feature points defined only by local, syntactic image calculations from other types of control points, such as those manually selected or on the basis of semantic characteristics. Feature points are determined by the application of an interest operator to the images for finding candidate feature points, and the subsequent extraction of feature descriptors to be used in computing pointwise similarity measures between corresponding features. After individual pairs of feature points are tentatively matched between images, the algorithm often applies a geometric consistency similarity measure to verify individual matches and reject outliers. (Note that this overlaps with area-based methods that register local regions or chips, essentially treating them as control points, so there is no clear distinction between feature- and area-based methods.) Feature-based methods can be quite complex, involving multiple passes of registration, geometric transformations that contain several parameters, various similarity measures, and different search approaches.

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We can categorize feature-point methods into two general classes: A class of methods that match dense sets of low-information-content features (typically edge points or wavelets), and a class of methods that match smaller sets of features that contain higher-information content, where the feature extraction and and the pointwise similar measure are more complex to evaluate. Methods based on dense feature sets may require less initial work but a more sophisticated geometric consistency measure (for defining a match), as well as a more intensive search effort on the feature sets. In the extreme, each feature point is considered individually without any additional information, and the problem reduces to a purely geometric one of geometric point set matching in a robust and efficient manner.

In dense feature point matching, the similarity measure is based on large sets or neighborhoods of point features. One approach is to apply binary or edge correlation to regions of points (Andrus *et al.*, 1975), but these measures do not allow significant local distortions in the feature sets. Huttenlocher *et al.* (1993) introduced an efficient algorithm for computing a variant of the Hausdorff distance measure, a geometric consistency measure based on the maximum of the minimum distances between points in the two sets. In effect, the Hausdorff measure evaluates a match based on the greatest remaining outlier. Mount *et al.* (1999) tested this variant on Landsat images using the original Huttenlocher branch and bound algorithm along with a Monte Carlo variation to accelerate the search. Chen and Huang (2007) presented a multilevel algorithm for the subpixel registration of high-resolution SAR data. They employed a Hausdorff metric with bi-tree searching to a pyramid of edge maps to compute a rough alignment. The SSDA area measure (mentioned in the previous subsection) was then employed to acquire tie-points, which were used to refine the alignment to subpixel accuracy.

A large number of papers have been written on the point pattern matching problem in the fields of image processing, pattern recognition, and computational geometry. In dense feature point matching, the similarity measure is based on large sets or neighborhoods of point features. One approach is to apply binary or edge correlation to regions of points (Andrus *et al.*, 1975), but these measures do not allow significant local distortions in the feature sets. Perhaps the simplest similarity measure among point sets involve the Hausdorff distance and its variants (Alt *et al.*, 1994; Chew *et al.*, 1997; Goodrich *et al.*, 1999; Huttenlocher *et al.*, 1993). The Hausdorff distance is a geometric measure based on the maximum of the minimum distances between points in the two sets. The standard notion of the Hausdorff distance, however, is not suitable for typical remote sensing applications, since it requires that every point (from at least one set) have a nearby matching point in the other set. Also, computing the optimal alignment of two-point sets even under the relatively simple Hausdorff distance is computationally intensive. In an attempt to alleviate the high complexity of point pattern matching, some

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researchers have considered *alignment-based* algorithms. These algorithms use alignments between small subsets of points to generate potential aligning transformations, the best of which are then subjected to more detailed analysis. Examples of these approaches include early work in the field of image processing (Stockman *et al*., 1982; Goshtasby and Stockman, 1985; Goshtasby *et al*., 1986) and more recent work in the field of computational geometry (Heffernan and Schirra 1994; Goodrich *et al*., 1999; Gavrilov *et al*., 2004; Cho and Mount, 2005; Choi and Goyal, 2006). Alignments can also be part of a more complex algorithm. For example, Kedem and Yarmovski (1996) presented a method for performing stereo matching under translation based on propagation of local matches for computing good global matches.

For remote sensing applications it is important that the distance measure be robust, in the sense that it is insensitive to a significant number of feature points from either set that have no matching point in the other set. Examples of a robust distance measures include the *partial Hausdorff distance* (PHD) introduced by Huttenlocher and Rucklidge (1993) and Huttenlocher *et al*. (1993), and symmetric and absolute differences discussed in Alt *et al*. (1996) and Hagedoorn and Veltkamp (1999). (See Chapter 8 for specific details.) Both measures were used within a branch-and-bound algorithmic framework for searching in transformation space. Drawing on this framework, Mount *et al*. (1999) proposed two ways of reducing the computational complexity of feature-point matching for image registration. Specifically, they considered an approximation branch-and-bound algorithm and a randomized, Monte Carlo algorithm (called *bounded alignment*) to further accelerate the search. A robust, hierarchical image registration scheme based on this algorithmic approach was applied by Netanyahu *et al*. (2004) for georegistering Landsat data to subpixel accuracy.

Also, Chen and Huang (2007) presented a multilevel algorithm for the subpixel registration of high-resolution SAR data. They employed a Hausdorff metric with bi-tree searching to a pyramid of edge maps to compute a rough alignment. The SSDA area measure (mentioned in the previous subsection) was then employed to acquire tie-points, which were used to refine the alignment to subpixel accuracy.

As noted above, large or moderate sets of feature points can be contaminated with many outliers and spurious points that do not have proper correspondences. Wong and Clausi (2007) described the system, Automatic Registration of Remote Sensing Images (ARRSI), which uses a variation on the *random sample consensus* (RANSAC) algorithm to match the control points. The system works by selecting random subsets of control points from which a tentative geometric transformation is computed. If the transformation consistently extends to a significant portion of the full set, then it is accepted as correct. The authors tested their approach on cross-band and cross-sensor Landsat and X-SAR images. Similarity, voting

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or accumulation schemes like the Hough transform (Yam and Davis, 1981; Li *et al*., 1995) can be used for potential matching of pairs to vote on the most likely transformation. In the Hough transform two feasible feature matches, whether correct or not, are used to compute a set of geometric transformations that map the feature in one image into the feature in the second image. Those sets are combined in a voting scheme, and the transformation chosen that gathers the most votes from the most potential matches. Correct matches are assumed to vote consistently for the correct match, while incorrect matches are assumed to vote for a random collection of inconsistent matches. Yang and Cohen (1999) computed affine invariants and convex hulls from local groups of points to drive the matching process.

Methods based on smaller, sparse sets of feature points require more effort to locate and describe the feature points. As mentioned, the first step is to apply an interest operator to the images for finding distinctive points. A syntactic interest operator is based only on general image properties, such as the magnitude of a local image derivative, or the persistence of the feature across scales. On the other hand, a semantic feature is based on the interpretation of the local image region as a road intersection, building corner, or other real world entity that can be stable over time. The same ground feature may be available for a long period of time for registration applications (Wang *et al*., 2005). In Subsection 3.3.2 we described six operational systems that used databases of manually selected ground control points (GCPs) represented as image chips. Remote sensing users often give semantic rules for the selection of GCPs (Sester *et al*., 1998; Wang *et al*., 2005). In other registration applications, for example, in robotic vision or medical imaging, the constant flow of new images emphasizes the use of real-time syntactic interest operators, while in remote sensing it is appropriate to invest considerable effort in collecting feature points for long-term use.

A preliminary phase in image registration involves the detection and extraction of image features that have suitable content for reliable matching. In other words, the original images are converted into feature sets for computing an optimal match. Syntactic interest operators look for distinctive regions with high-content information that can be localized in two directions simultaneously, such as corners or line intersections. They do so by computing local image properties (such as first and second image derivatives). Commonly used operators are due to Harris and Stephens (1988) and Förstner and Gülch (1987). Schmid *et al*. (2000) systematically reviewed and evaluated a number of interest operators and concluded, based on the criterion they defined, that the Harris operator was the most repeatable and informative. Mikolajczyk and Schmid (2004) extended the Harris detector to an affine invariant, scale space version (Harris-affine), that detects local maxima of the detector at multiple image scales. Mikolajczyk *et al*. (2005) reviewed six different affine invariant operators, including the Harris-affine, and concluded under what conditions each operator was most useful. Kelman *et al*. (2007) evaluated the three interest operators: Laplacian-of-Gaussian, Harris, and *maximally stable extremal regions* (MSERs), for the repeatability of their locations and orientations. The topic is rich enough to support a book surveying interest and feature operators (Tuytelaars and Mikolajczyk, 2008). However, much of the literature does not account for the complexity of remote sensing imagery. Hong *et al*. (2006) emphasized the complexity of extracting GCPs in remote sensing data, as the extraction operator needs to account for the physical imaging models of the sensor, the satellite orbit, and the terrain's DEM to accurately recover invariant feature points in SAR and optical images.

Once feature points have been detected, a feature descriptor operator extracts local information to define a similarity measure for point-to-point matching. By reducing a neighborhood to a smaller set of descriptors relatively invariant to geometric and radiometric transformations, the matching process can be made more efficient and robust. Local descriptors include moments of intensity or gradient information, local histograms of intensity of gradients, or geometric relationships between local edges.

Lowe defined the *scale-invariant feature transform* (SIFT) (Lowe, 1999; Lowe, 2004), which is a weighted, normalized histogram of local gradient edge directions invariant to minor affine transformations. The SIFT operator has been widely used in a number of registration applications. Yang *et al*. (2006) used SIFT in an extension of the *dual bootstrap iterative closest point* (ICP) algorithm, originally developed for retinal image registration. As originally defined by Stewart *et al*. (2003), dual bootstrap is a robust algorithm that proved successful on more than 99.5% of retinal image pairs, and 100% on pairs with an overlap of at least 35%. The dual bootstrap ICP algorithm is a multistage procedure. It starts by matching interest points found in retinal vessel bifurcations. In the retinal version, the invariants used were the ratio of blood vessel widths and their orientations, yielding a five-component feature-point descriptor. The SIFT operator was then employed to obtain an extended version that performed successfully on the challenging image pairs that were experimented with. Li *et al*. (2009) have recently refined the SIFT operator to increase its robustness and applied it to cross-band and cross-sensor satellite images. The reader is referred to the following additional relevant papers: Ke and Sukthankar (2004); Mikolajczyk and Schmid (2004); Mikolajczyk and Schmid (2005); Mikolajczyk *et al*. (2005); and Dufournaud *et al*. (2004).

In remote sensing, there have been a number of applications of feature point detectors and descriptors. Igbokwe (1999) performed subpixel registration of Landsat Multi Spectral Scanner (MSS) and TM data to 0.28 pixel accuracy. They located feature points using the interest operator, *target defined ground operator* (TDGO), described in Chen and Lee (1992), and then applied least-squares iterative

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subpixel matching in local regions. Grodecki and Lutes (2005) performed registration for redundant validation of IKONOS geometric calibration. They used two test sites with features points selected manually and automatically with the Förstner and Gülch interest operator. Bentoutou *et al*. (2005) registered SPOT and SAR images to subpixel accuracy, with a root mean square error (RMSE) of 0.2 pixels. They located feature points using an enhanced Harris detector, and then matched the points with affine invariant region descriptors with a subpixel interpolation of the similarity measure. Carrion *et al*. (2002) described the GEOREF system that the authors tested with Landsat imagery. In the GEOREF system, features extracted by the Förstner operator are located and matched at multiple levels using an image pyramid. An interesting twist is that once two feature points are matched, the match is refined in a local neighborhood around the feature point by a least-squares, area-based method. Here, feature- and area-based approaches are combined to best match two feature points.

At an extreme for the semantic content of features, Growe and Tönjes (1997) used a semantic, expert system approach to segment and understand image features for matching. Raw, low-level image features like edges were interpreted through a semantic net as meaningful high-level features like roads and houses. They matched the resulting feature with the A* algorithm to control search.

Arevalo and Gonzalez (2008b) presented a complex algorithm for a nonrigid, piecewise local polynomial geometric transformation that integrates a number of the methods explained above. Control points were detected by the Harris operator and then matched to subpixel accuracy using gradient descent. An initial transform was then estimated with RANSAC, followed by a computation of a triangular mesh of the control points. Since some of the triangular regions in the mesh may overlap discontinuities, such as building edges, the mesh was refined through an iterative process to swap edges until regions became more homogenous. The homogeneity was evaluated by a mutual information measure.

3.3.6 Contour- and region-based approaches

Contour- and region-based approaches use extended features such as lines, contours, and regions. These extended features, which can be obtained by connecting edge points, or segmenting the images into compact regions, can prove robust in cross-band and cross-sensor registration. Contour- and region-based approaches are particularly useful for water features, such as lakes, rivers, and coastlines, or for man-made structures like roads. However, these features are all subject to change over time so they cannot be assumed constant.

Line matching, based on linear features extracted in IKONOS and SPOT imagery, was described in Habib and Alruzouq (2004) and Habib and Al-Ruzouq

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(2005). Manually outlined linear segments of road networks were provided as input. The collections of these line primitives were then compared by a *modified iterated Hough transform* (MIHT) to compute the desired affine transformation. Wang and Chen (1997) performed line matching by using invariant properties of line segments.

Contour matching uses pixel sequences or polynomial curves fit to edge data, such as *non-uniform rational B-splines* (NURBS), to compute optimal geometric transformations for matching and registration. See, for example, Li *et al*. (1995), Carr *et al*. (1997), Eugenio and Marques (2003), and Pan *et al*. (2008). We briefly review a few related methods below. Dai and Khorram (1999) derived a contour-based matching scheme, and demonstrated its applicability on Landsat TM images. Edge pixels were first extracted by a Laplacian-of-Gaussian (LoG) zero-crossing operator, and then linked/sorted to detect contours. Regions defined by these closed contours were then matched (in feature space), combining invariant moments of the planar regions and chain-code representations of their contours. Finally, the initial registration step was refined (in image space) by matching a set of GCPs defined by centers of gravity of matched regions. Subpixel accuracy of roughly 0.2 pixels (in terms of the RMSE at the GCPs) was reported. Similarly, Eugenio and Marques (2003) registered AVHRR and SeaWiFS images by extracting closed and open-boundary contours of SeaWiFS island targets. They combined invariant region descriptors, individual contour matching, and a final global registration step on all contour points. Govindu and Shekhar (1999) carried out image matching by using contour invariants under affine transformations for both connected and disconnected contours. Xia and Liu (2004) performed efficient matching by using "super-curves," which are formed by superimposing pairs of affine-related curves in one coordinate system, and then finding simultaneously their B-spline approximations and registration.

Madani *et al*. (2004) described the operational AutoLandmark system for registration of the Geostationary Operational Environmental Satellite (GOES) imagery. GOES I-M is a series of 7-band weather satellites, which were launched from 1994 to 2001. Since the satellite images contain considerable ocean regions, the registration could be complicated. On the other hand, this type of image could support a coastline matching strategy. Note that the daily warming/cooling cycle affects the infrared bands, in the sense that land and water can reverse in radiation, causing coastal edges to invert, migrate, or even disappear. To avoid these radiometric effects, the registration was performed on a database of coastlines, which were represented in vector format. Specifically, 24×24 (or 96×96) landmark neighborhoods were extracted from the sensed image, and edge pixels (for each neighborhood) were detected using the Sobel operator. The edge map obtained was matched against a binary image rasterized from the coastline vector database,

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taking the sum of relevant edge strengths as a measure of correlation, and limiting the transformation to translations only. Cloud regions were masked out along the process. Bisection search was finally used to obtain subpixel accuracy. The overall quality measure of the registration was defined as a combination of the edge correlation, the fraction of cloud contamination, and the contrast (and possibly illumination) in the image.

Registration based on region matching uses local patches or closed boundary curves, found by intensity segmentation or curve extraction. Dare and Dowman (2001) segmented SPOT and SAR images into homogenous patches, and then used straightforward parameters like area, perimeter, width, height, and overlapping area to compute a similarity measure between regions. Following this, they matched strong edge pixels by dynamic programming. Flusser and Suk (1994) detected close boundaries (from edge pixels obtained by the Sobel operator) and then used affine invariant moments of closed boundaries to register SPOT and Landsat images to subpixel accuracy under an affine transformation. See also Goshtasby *et al*. (1986) and Yuan *et al*. (2006) for additional related papers.

3.4 Geometric transformations

Image registration assumes a coherent geometric transformation between the sensed and reference images. If sufficient knowledge is available about the imaging model of the sensor, geometric distortions from satellite orbit and attitude variations, atmospheric effects, and topographic relief, then a physically accurate model of the transformation can be constructed, and an appropriate algorithm for the model can be chosen (Huseby *et al*., 2005). If the above information is not available or is too complex, an approximate empirical model can be used. A physically accurate model is of course most suitable for refining a raw remote sensing image into an orthoimage, that is, a distortion-free version of the image that represents an ideal projection onto geodetic coordinates of the ground plane. Fully corrected orthoimages are best suited for integration into geographic information systems and fusion with all types of geographic data. Toutin (2004) noted several factors that drive the use of physical models of higher accuracy for orthorectification. These factors include higher-resolution sensors, additional imagery taken from off-nadir viewing angles, greater precision needed for digital processing, and the fusion of data from multiple image and vector sources. Armston *et al*. (2002) compared the use of physical and empirical geometric models in landcover mapping in Australia, using models available in commercial software packages. They evaluated the models used on field-collected GCPs and manually selected tie-points initially found using syntactic and semantic properties and then refining the GCP matches by image chip correlation. Using the RMSE of the GCPs as a quality metric,

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they found that empirical rational polynomial models gave higher errors than the physical models.

Still, the transformations used in the matching phase of image registration are usually based on empirical models that offer sufficient accuracy for the task but are not physically accurate. In particular, when an image registration algorithm is based on matching small image regions as chips or control points, empirical models of a simple geometric transformation as translation can be sufficiently accurate even without taking into account additional elements such as perspective. Thus, many image registration algorithms use empirical, low-order geometric models over small regions as chips or control points, and then use the control points to compute more accurate, parametric geometric models of higher order. Many algorithmic techniques, such as those based on numerical optimization or the Fourier transform, are primarily designed for the explicit recovery of the parameters of a low-order model, such as translation, rotation, and scale. Empirical models include:

(1) Rotation, scale, and translation (RST), i.e., transformations with four parameters. The RST model is a useful subset of the affine transformations.
(2) Affine transformation of six parameters.
(3) Projective transformation of eight parameters.
(4) Homography, which consists of eight degrees of freedom.
(5) Higher order 2D and 3D polynomial functions.
(6) Rational polynomials.

There are many sources of information on the mathematical details of geometric transformations, and we do not pursue the details here. For a general treatment, the reader is referred to Goshtasby (2005), and for details on projective and homography transformations the reader is referred to Faugeras (1993). Toutin (2004) is a review article on empirical and physical geometric models, including rational polynomials.

While the geometric transformations used for local matching are usually global and rigid, nonrigid or locally rigid transforms are important to account for distortions that vary across an image pair. Here, global means a single transformation is used across the entire image. Sharp topography, such as tall buildings and steep natural features, can introduce significant local perspective effects that are not accounted for in global, low-order transformations. Goshtasby (1988) introduced methods for piecewise local nonrigid methods, in which the images are segmented into regions in which local polynomial functions are used. In Zagorchev and Goshtasby (2006), the authors reviewed and compared these methods, including thin-plate spline, multiquadric, piecewise linear and weighted mean transformations. Arevalo and Gonzalez (2008a) compared nonrigid geometric transformations on QuickBird imagery. These transformations included piecewise (linear or cubic) functions, weighted mean functions, radial basis functions, and B-spline functions.

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Approximate image alignment was first done manually. This was then refined using feature points that were obtained due to the Harris detector. Finally, gradient descent was used to achieve subpixel accuracy. The authors found the piecewise polynomial model superior on nonorthorectified imagery, and global fourth-order polynomials most adequate for orthorectified images.

3.5 Radiometric transformations and resampling

Under the correct geometric transformation, two corresponding image points should have related intensity values. If we assume that the corresponding image points represent the same ground feature, then the radiometric readings of that feature should have some consistency between two sensing events. That consistency or relationship confounds a number of factors, for example, the radiometric responses of the two sensors, the time of day and other environmental factors, the angle of view, the specular response of the ground feature, etc. All this is further confounded by multiband sensors, so in registering two images we may be relating two spectral bands which may or may not overlap. If we can account for all these factors, we can build a radiometric model (or function g) that maps intensities in one image to another, and use this model in designing a registration algorithm. However, few image registration algorithms use explicit radiometric relationships during the matching process. This is because the relationship may be difficult to calibrate, the algorithm may be used on many sensors (so a single relationship is not useful or appropriate), and the confounding environmental factors may overwhelm the relationship. Instead, most registration algorithms base their similarity measures on general assumptions made about the relationship, either explicitly or implicitly. Thus, choosing the appropriate assumptions is important in algorithm design and selection. The assumptions made about the radiometric model were classified in Roche *et al*. (2000) as follows:

(1) Identity relationship, i.e., assuming that the image intensity is invariant. This assumption is explicit in methods based on similarity measures that sum directly the square of absolute values of intensity differences.
(2) Affine relationship, i.e., assuming that the intensities differ by a linear gain and bias. This assumption is implicit in methods based on the correlation coefficient or least-squares minimization.
(3) Functional relationship, i.e., assuming that the intensities differ by a general function. This assumption is implicit in a few measures, including the correlation and Woods measures.
(4) Statistical relationship, i.e., assuming that while individual corresponding points may have differing intensities, in local neighborhoods they are drawn from the same statistical distribution. This is implicit in mutual information and similar approaches.

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There are algorithms that integrate an explicit radiometric term during the matching process. Georgescu and Meer (2004) integrated a radiometric correction with robust M-estimators in a gradient descent approach. Thévenaz *et al*. (1998) integrated an exponential gamma model in a least-squares gradient descent approach, while Bartoli (2008) used a general multiband affine relationship to combine different color channels dynamically during gradient descent registration. Orchard (2007) used linear regression to estimate a piecewise linear relationship between semi-registered images. Hong and Zhang (2008) considered different radiometric normalization methods for high-resolution satellite images, such as scattergrams and histogram matching, to bring different sensors into the same color metric. This approach might be appropriate to preprocess images before matching.

Since digital images are represented by values on a discrete grid, typically a uniformly spaced rectangular grid, for one image to be geometrically transformed to match another, the values have to be resampled to the new grid locations. This can be done for two purposes: (1) Obtain an end product of image registration for further use in remote sensing applications, and (2) produce intermediate images (during the registration process) for incremental use, for example, an iterative computation of the geometric transformation. Greater care must be taken in the former case than in the latter, since values in the final image product may be used in further image analysis steps, while the intermediate resampled images are only a means to registration and will be deleted after use. As a result, an image registration system may use multiple resampling techniques. In both cases, it is important to avoid resampling artifacts, as this may degrade the data itself or the accuracy of the image registration.

Resampling is commonly done by reverse sampling of image values to remap the sensed image to a new image. If $f(u, v)$ is the geometric transformation that maps the sensed image into the reference image, then the inverse transformation $f^{-1}(x, y)$ is applied to map a pixel in the new sensed image to a subpixel location (u', v') between four surrounding input pixels in the grid of the old sensed image. (See Fig. 3.1.) The values of these four pixels (or pixels in a larger surrounding neighborhood) are then interpolated to compute the new pixel value. Increasing fidelity of the interpolation usually incurs greater computational cost.

The basic interpolation methods below are well documented in Goshtasby (2005). These methods include, in order of computational effort:

(1) *Nearest neighbor*, where the output pixel is given the value of the input pixel whose location is closest to the reverse sampled position (x, y). The advantage of nearest neighbor resampling is that the output image only contains intensity values present in the original image. However, it can produce aliasing “jaggies,” particularly with rotation.

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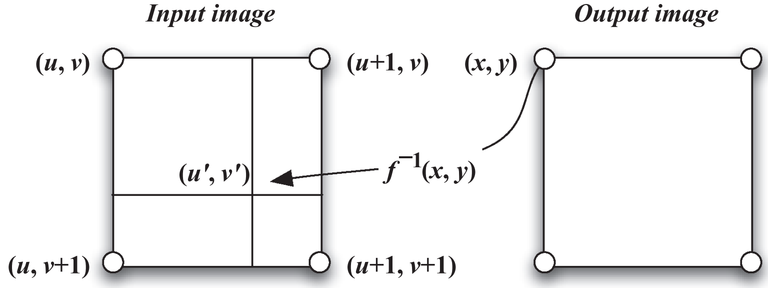

Figure 3.1. Resampling neighborhood.

(2) *Bilinear*, where the output pixel value is a linear interpolation of the local neighborhood, usually the four surrounding input pixels. The advantage of bilinear interpolation is that it is fast. Also, its results are visually similar to those obtained by more complex interpolators, although it is not as accurate as the bicubic interpolator or the other higher-order methods.
(3) *Bicubic*, where the output pixel value is obtained by a cubic polynomial interpolation of the values in a local neighborhood.
(4) *Spline*, where the output pixel value is computed by a polynomial spline interpolation (e.g., B-spline) of the local neighborhood.
(5) *Sinc function*, where the output pixel value is obtained by an interpolation based on the sinc function, $\sin(x, y)/r$ (where $r = \sqrt{x^2 + y^2}$) over a local neighborhood.

Each method can result in resampling (or interpolation) artifacts in the resulting image and in similarity measures derived from the image values. Inglada *et al*. (2007) reported on artifacts from bilinear, bicubic, and sinc interpolators, and noted that the interpolators had the effect of blurring the sensed image, although the magnitude of the blurring depended on the subpixel value of the shift. For example, integral shifts land exactly on a pixel and result in little blurring, while shifts of half a pixel result in maximum blurring. This can result in a "scalloping" effect that introduces artificial local maxima at subpixel shifts in similarity measures, such as mutual information (Pluim *et al*., 2000; Tsao, 2003; Thévenaz *et al*., 2008) and correlation measures (Salvado and Wilson, 2007; Rohde *et al*., 2008). These artifacts can be addressed by careful prefiltering to reduce noise (Salvado and Wilson, 2007) or by proper randomized sampling (Tsao, 2003; Thévenaz *et al*., 2008). However, this must be done carefully, as noise blurring contributes to the scalloping effect.

3.6 Evaluation of image registration algorithms

A typical satellite is very expensive to develop and operate, and the data produced can influence major governmental and industrial decisions on land use, crop

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production and other economic or political issues. Given the commercial and social impacts of research and development in remote sensing, proper evaluation of image registration reliability and accuracy is thus an essential component.

In general, performance evaluation may be associated with different aspects of the image analysis process. The image registration research community, by and large, is concerned with the derivation of proper metrics for technique evaluation and ranking. This community works to evaluate and rank basic registration algorithms, with the objective of choosing the best registration algorithms for general classes of data. On the other hand, the operational community focuses on validating the performance specifications of its image products, and end users focus on whether the image products meet their needs for commercial and scientific analysis. They are more concerned with the quality of the ultimate data of interest than with the best registration algorithm. Ideally, metrics for image registration evaluation would articulate and incorporate end-user requirements so the imaging community could better serve and communicate with end users.

The evaluation of image registration is relatively well established within the medical imaging community, which has access to techniques that are not as easily available in remote sensing. For example, in medical image registration, ground truth (or "gold standards") are produced by introducing fiducial marks into images or using phantom targets (Penney *et al*., 1998), which facilitates algorithm comparison. In contrast, it is harder in remote sensing to produce ground truth for naturally collected data.

In this section we look into the issue of registration evaluation in two respects. First, we review evaluation aspects concerning the operational and user communities, for example, the impact of registration errors on operational teams and practitioners. Secondly, we discuss evaluation issues concerning the image registration algorithms themselves.

3.6.1 Operational and user oriented evaluation

How good must an image registration algorithm have to be? To answer this, one should consider the application in question. If used to mosaic multiple images for a visual display, the requirements from an algorithm may be less rigorous than for aligning two images to detect small changes in vegetative cover. Operational satellite teams have performance requirements set during the system design, which they work to meet. Users set requirements that come from the needs of their analytic techniques. Both sets of requirements can be informative in the design and evaluation of registration algorithms.

Accuracy needs of image registration for change detection has been one of the most studied application needs. Townshend *et al*. (1992) studied four regions in

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Landsat TM imagery, and found that to keep the Normalized Difference Vegetation Index (NDVI) pixel-based change estimations down to an error of 10%, the registration subpixel accuracy had to be within 0.2 pixels. Studying, however, three additional homogenous, arid regions, they found that the registration accuracy required for the above 10% error was within 0.5 to 1.0 pixels. For detection of changes over time, Dai and Khorram (1998) showed that a registration accuracy of less than 1/5 of a pixel was required to achieve a change detection error of less than 10%. Other articles on the impact of misregistration on change measurements include, for example, Roy (2000), Salas *et al*. (2003), and Wang and Ellis (2005a). Bruzzone and Cossu (2003) formulated an approach to evaluate change detection that adapts to and mitigates misregistration errors. Other issues that influence the impact of misregistration on change detection include the number of classes, region heterogeneity (Verbyla and Boles, 2000), and the resolution at which change detection is computed (Wang and Ellis, 2005b). In the latter paper the authors considered how measures of region heterogeneity in high-resolution imagery interact with change resolution and misregistration errors. Specifically, these authors have considered how to adapt to misregistration errors either by estimating them or lowering the resolution of change detection (Verbyla and Boles, 2000; Bruzzone and Cossu, 2003; Wang and Ellis, 2005b).

Another well-studied area is the evaluation of errors in orthorectified imagery, which is critical for operational teams. Zhou and Li (2000), Toutin (2003), Grodecki and Lutes (2005), and Wang *et al*. (2005) all addressed the geometric accuracy of IKONOS images. Looking at IKONOS panchromatic and multiband images over seven study sites in Canada, Toutin investigated the relationship between the accuracy of GCPs and its effect on precision correction of IKONOS for orthorectification. He found that the accuracy of GCPs affected how many of them were required to compute accurate geometric models for orthorectification, but that the error sensitivity of the model was low and good results could be obtained despite inaccurate GCPs. Zhou and Li (2000) performed a similar analysis to compare the influence of the number of GCPs, their distribution, and their measurement error, as well as the order of the geometric correction polynomial on the error obtained. Grodecki and Lutes (2005) performed backup validation of IKONOS geometric calibration through manually and automatically selected GCPs, and found that it met the operational specifications. Wang *et al*. (2005) looked specifically at four geometric models (translation, translation and scale, affine, and second-order polynomial models) to further reduce ground point errors in IKONOS, with the objective of determining if lower cost IKONOS geosatellite imagery could be adequately refined for practical use.

Ideally, there should be mechanisms for the propagation analysis of image registration errors through the processing of remotely sensed images. Krupnik (2003)

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developed a mathematical formulation for error propagation in orthorectified image production for predicting the accuracy of the orthoimage obtained. The formulation combined several parameters, such as the accuracy of the digital elevation model, control points, and image measurements, as well as the configuration of fiducial, tie, and control points, and the ground slope. Poe *et al*. (2008) developed a similar formulation for geolocation errors observed with data from the Special Sensor Microwave Imager/Sounder (F-16 SSMIS) radiometer observations.

3.6.2 Algorithm evaluation

A traditional means of evaluating registration and geolocation accuracy is through the residual error of manually selected control points, that is, their root mean square error (RMSE). The assessment of transformations produced by manually selected CPs is often judged by repeatability and precision rather than formal accuracy, as the RMSE and variance evaluate the tightness of the CP residuals in the absence of ground truth data. This is often done by computing residuals under a transformation in question with respect to a separate set of independent check points using *hold-out validation* (HOV), or by recomputing the residual of one control point via *leave-one-out cross-validation* (LOOCV) (Brovelli *et al*. 2006). (In each iteration, a different control point is left out.) In general, the accuracy increases with the number of CPs up to a diminishing return (Toutin, 2004; Wang and Ellis, 2005a). Spatial and orientation distributions of residuals have also been considered (Buiten and van Putten, 1997; Fitzpatrick *et al*., 1998; Armston *et al*., 2002). Felicsimo *et al*. (2006) verified registration by careful analysis of residuals, looking at homogeneity and isotropy of spatial uncertainty by means of GPS kinematic check lines and circular statistics.

In addition to evaluating the end result of registration algorithms, image registration research can concentrate on evaluating alternative elements of registration algorithms. Maes *et al*. (1999) evaluated alternative optimization methods for use with mutual information. Recently, Klein *et al.* have also evaluated optimization methods (Klein *et al*., 2007); (Klein *et al*., 2009). Jenkinson and Smith (2001) looked at the efficiency and robustness of global optimization schemes, observing that local optimization schemes often did not find the optimum in their test medical imagery. They also tested alternative statistical similarity measures. A number of other articles focused on surveying, comparing, and unifying similarity measures. Kirby *et al*. (2006) implemented and compared several measures on images from the airborne Variable Interference Filter Imaging Spectrometer (VIFIS). The measures included normalized correlation, ordinal correlation, and invariant intensity moments. They found normalized correlation the most effective. In a medical application, Skerl *et al*. (2006) proposed an evaluation protocol

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for evaluation of similarity measures independent of the optimization procedure used. They implemented nine different multimodal statistical measures, including mutual information, normalized mutual information, correlation ratio and Woods criterion, and applied them to different image types. The authors compared the performance obtained with these measures with respect to several parameters, such as accuracy, capture, distinctiveness of the global optimum, and robustness. Their results varied for the image types studied, so their protocol can be seen as a way of recommending a similarity measure according to the relevant application. Inglada and Giros (2004) systematically investigated the application of different similarity measures to multisensor satellite registration of SPOT and ERS-2 data, including correlation, correlation ratio, normalized standard deviation, mutual information, and the related Kolmogorov measure. Pluim *et al*. (2004) compared the performance with respect to seven different information-theoretic similarity measures (including mutual information) on medical images. They considered specifically issues, such as smoothness of the optimization surface, accuracy, and optimization difficulty.

One problem in evaluating image registration algorithms is the comparison of apples to oranges, that is, the comparison of algorithms implemented by different research groups using software components that may not be directly equivalent. It can be hard to compare search strategies, for example, while holding all other elements of the algorithm fixed, as two implementations may differ slightly in edge detection or other processing details. In Le Moigne *et al*. (2003), the authors presented a modular framework for implementing several algorithms in a common software system so as to hold processing details fixed, and to allow systematic variation on elements such as feature extraction, similarity measure and search strategy. This approach is often taken for comparison of a single element, such as variations in search or similarity measure, but rarely as to allow variation of several elements. A second problem for evaluation of registration algorithms is the development of useful metrics for algorithm performance. In Le Moigne *et al*. (2004), the authors extended the previously described general framework to studies of the sensitivity of registration algorithms to initial estimates of transformation parameters. The study found that the domains of parameter convergence for different algorithms can be complex in shape and extent.

Change detection, that is, the recovery of significant temporal or modal changes between two images, is an important analytic tool in remote sensing, which is closely related to similarity measure. An underlying assumption associated with similarity measure is that two corresponding image regions are related. This assumption is invalid, however, under various circumstances, for example, a forest has been cut down or a field has been converted to houses. In other words, whereas

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most of the image may match perfectly, certain isolated regions do not. If these regions can be detected as outliers, then the registration algorithm can ignore them. For example, cloud detection and masking are essential elements. Radke *et al*. (2005) surveyed change detection algorithms, while Hasler *et al*. (2003) modeled outliers by finding regions with differing statistics. Im *et al*. (2007) demonstrated change detection using correlation image analysis and image segmentation.

3.7 Summary

Image registration is a key, essential element in analysis of Earth remote sensing imagery. Registration is critical both for initial processing of raw satellite data for validation, preparation, and distribution of image products, and for end-user processing of those image products for data fusion, change detection, cartography, and other analyses. Given the increasing, immense rate of image capture by satellite systems and the growing complexity of end-user analyses, there is a stronger need for accurate, validated, fully automatic, and efficient registration algorithms and software systems. This chapter has surveyed the recent image registration literature to provide an overview of the current best approaches to this broad, multifaceted problem.

The image registration literature continues to grow, and the reader may wish to pursue more recent publications in specialized venues. General surveys and books on image registration were previously mentioned in the introduction. Examples of publication venues that frequently include articles on image registration for remote sensing are the *IEEE Transactions on Geoscience and Remote Sensing* (*TGRS*) and the *IEEE Transactions on Image Processing* (*TIP*), which deal, respectively, with remote sensing issues and image processing and mathematical models. Other venues where readers can keep their knowledge up-to-date include the yearly *IEEE International Geoscience and Remote Sensing Symposium* (*IGARSS*), the *American Geophysical Union* (*AGU*) Fall and Spring meetings, the annual *IEEE Conference on Computer Vision and Pattern Recognition* (*CVPR*), the *IEEE International Conference on Image Processing* (*ICIP*), and the conferences on *Neural Information Processing Systems* (*NIPS*). This short list of venues provides merely a starting point for further exploration of numerous relevant papers in the area of image registration.

References

Abdelfattah, R. and Nicolas, J. M. (2005). InSAR image co-registration using the Fourier-Mellin transform. *International Journal of Remote Sensing*, **26**(13), 2865–2876.

P1: SFK Trim: 174mm × 247mm Top: 0.553in Gutter: 0.747in
CUUK1136-03 cuuk1136/Le-Moigne ISBN: 978 0 521 51611 2 September 15, 2010 10:17

Ackerman, F. (1984). Digital image correlation: Performance and potential application in photogrammetry. *The Photogrammetric Record*, **11**(64), 429–439.

Alt, H., Aichholzer, O., and Rote, G. (1994). Matching shapes with a reference point. In *Proceedings of the Tenth Annual ACM Symposium on Computational Geometry*, Stony Brook, NY, pp. 85–91.

Alt, H., Fuchs, U., Rote, G., and Weber, G. (1996). Matching convex shapes with respect to the symmetric difference. In *Proceedings of the Fourth Annual European Symposium on Algorithms*. London: Springer-Verlag, pp. 320–333.

Althof, R. J., Wind, M. G., and Dobbins, J. T. I. (1997). A rapid and automatic image registration algorithm with subpixel accuracy. *IEEE Transactions on Medical Imaging*, **16**(2), 308–316.

Andrus, J., Campbell, C., and Jayroe, R. (1975). Digital image registration method using boundary maps. *IEEE Transactions on Computers*, **24**(9), 935–940.

Arevalo, V. and Gonzalez, J. (2008a). An experimental evaluation of non-rigid registration techniques on QuickBird satellite imagery. *International Journal of Remote Sensing*, **29**(2), 513–527.

Arevalo, V. and Gonzalez, J. (2008b). Improving piecewise linear registration of high-resolution satellite images through mesh optimization. *IEEE Transactions on Geoscience and Remote Sensing*, **46**(11), 3792–3803.

Armston, J., Danaher, T., Goulevitch, B., and Byrne, M. (2002). Geometric correction of Landsat MSS, TM, and ETM+ imagery for mapping of woody vegetation cover and change detection in Queensland. In *Proceedings of the Eleventh Australasian Remote Sensing and Photogrammetry Conference*, Brisbane, Queensland, Australia, pp. 1–23.

Arya, K., Gupta, P., Kalra, P., and Mitra, P. (2007). Image registration using robust M-estimators. *Pattern Recognition Letters*, **28**, 1957–1968.

Baillarin, S., Bouillon, A., Bernard, M., and Chikhi, M. (2005). Using a three dimensional spatial database to orthorectify automatically remote sensing images. In *Proceedings of the ISPRS Hangzhou 2005 Workshop on Service and Application of Spatial Data Infrastructure*, Hangzhou, China, pp. 89–93.

Baker, S. and Matthews, I. (2001). Equivalence and efficiency of image alignment algorithms. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, Kauai, Hawaii, pp. 1090–1097.

Bardera, A., Feixas, M., and Boada, I. (2004). Normalized similarity measures for medical image registration. In *Proceedings of the SPIE International Symposium on Medical Imaging*, San Diego, CA, pp. 108–118.

Barnea, D. J. and Silverman, H. F. (1972). A class of algorithms for fast digital image registration. *IEEE Transactions on Computing*, **21**, 179–186.

Bartoli, A. (2008). Groupwise geometric and photometric direct image registration. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **30**(12), 2098–2108.

Bentoutou, Y., Taleb, N., Kpalma, K., and Ronsin, J. (2005). An automatic image registration for applications in remote sensing. *IEEE Transactions on Geoscience and Remote Sensing*, **43**(9), 2127–2137.

Brovelli, M. A., Crespi, M., Fratarcangeli, F., Giannone, F., and Realin, E. (2006). Accuracy assessment of high resolution satellite imagery by leave-one-out method. In *Proceedings of the Seventh International Symposium on Spatial Accuracy Assessment in Natural Resources and Environmental Science*, Lisbon, Portugal, pp. 533–542.

Brown, L. G. (1992). A survey of image registration techniques. *ACM Computing Surveys*, **24**(4), 325–376.

Bruzzone, L. and Cossu, R. (2003). An adaptive approach to reducing registration noise effects in unsupervised change detection. *IEEE Transactions on Geoscience and Remote Sensing*, **41**(11), 2455–2465.

Buiten, H. J. and van Putten, B. (1997). Quality assessment of remote sensing image registration: Analysis and testing of control point residuals. *ISPRS Journal of Photogrammetry and Remote Sensing*, **52**, 57–73.

Cain, S., Hayat, M., and Armstrong, E. (2001). Projection-based image registration in the presence of fixed-pattern noise. *IEEE Transactions on Image Processing*, **10**(12), 1860–1872.

Cariou, C. and Chehdi, K. (2008). Automatic georeferencing of airborne pushbroom scanner images with missing ancillary data using mutual information. *IEEE Transactions on Geoscience and Remote Sensing*, **46**(5), 1290–1300.

Carr, J. L., Mangolini, M., Pourcelot, B., and Baucom, A. W. (1997). Automated and robust image geometry measurement techniques with application to meteorological satellite imaging. In *Proceedings of the CESDIS Image Registration Workshop*, NASA Goddard Space Flight Center, Greenbelt, MD, pp. 89–99.

Carrion, D., Gianinetto, M., and Scaioni, M. (2002). GEOREF: A software for improving the use of remote sensing images in environmental applications. In *Proceedings of the First Biennial Meeting of the International Environmental Modelling and Software Society*, Vol. 3, Lugano, Switzerland, pp. 360–365.

Ceccarelli, M., di Bisceglie, M., Galdi, C., Giangregorio, G., and Liberata, U. S. (2008). Image registration using non-linear diffusion. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium*, Boston, MA, pp. 220–223.

Chen, H. M., Arora, M. K., and Varshney, P. K. (2003). Mutual information-based image registration for remote sensing data. *International Journal of Remote Sensing*, **24**(18), 3701–3706.

Chen, H., Varshney, P. K., and Arora, M. K. (2003). Performance of mutual information similarity measure for registration of multitemporal remote sensing images. *IEEE Transactions on Geoscience and Remote Sensing*, **41**(11), 2445–2454.

Chen, L.-C. and Lee, L.-H. (1992). Progressive generation of control frame works for image registration. *Photogrammetric Engineering & Remote Sensing*, **58**(9), 1321–1328.

Chen, Q., Defrise, M., and Deconinck, F. (1994). Symmetric phase-only matched filtering of Fourier-Mellin transforms for images registration and recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **16**(12), 1156–1168.

Chen, T. and Huang, T. S. (2007). Optimizing image registration by mutually exclusive scale components. In *Proceedings of the IEEE International Conference on Computer Vision*, Rio de Janeiro, Brazil, pp. 1–8.

Chew, L. P., Goodrich, M. T., Huttenlocher, D. P., Kedem, K., Kleinberg, J. M., and Kravets, D. (1997). Geometric pattern matching under Euclidean motion. *Computational Geometry Theory and Applications*, **7**, 113–124.

Cho, M. and Mount, D. M. (2005). Improved approximation bounds for planar point pattern matching. In *Proceedings of the Ninth Workshop on Algorithms and Data Structures*, Waterloo, Canada; *Lecture Notes in Computer Science*, Springer-Verlag, Vol. 3608, pp. 432–443.

Choi, V. and Goyal, N. (2006). An efficient approximation algorithm for point pattern matching under noise. In *Proceedings of the Seventh Latin American Theoretical Informatics Symposium*, Valdivia, Chile; *Lecture Notes in Computer Science*, Springer-Verlag, Vol. 3887, pp. 298–310.

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Cole-Rhodes, A., Johnson, K., Le Moigne, J., and Zavorin, I. (2003). Multiresolution registration of remote sensing images using stochastic gradient. *IEEE Transactions on Image Processing*, **12**(12), 1495–1511.

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

Dai, X. L. and Khorram, S. (1999). A feature-based image registration algorithm using improved chain-code representation combined with invariant moments. *IEEE Transactions on Geoscience and Remote Sensing*, **37**(5), 2351–2362.

Dare, P. and Dowman, I. (2001). An improved model for automatic feature-based registration of SAR and SPOT images. *ISPRS Journal of Photogrammetry and Remote Sensing*, **56**(1), 13–28.

De Castro, E. and Morandi, C. (1987). Registration of translated and rotated images using finite Fourier transforms. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **9**(5), 700–703.

Dewdney, A. K. (1978). Analysis of a steepest-descent image-matching algorithm. *Pattern Recognition*, **10**(1), 31–39.

Dowson, N. and Bowden, R. (2006). A unifying framework for mutual information methods for use in non-linear optimisation. In *Proceedings of the Ninth European Conference on Computer Vision*, Graz, Austria; *Lecture Notes in Computer Science*, Springer, Vol. 3951, pp. 365–378.

Dowson, N., Kadir, T., and Bowden, R. (2008). Estimating the joint statistics of images using nonparametric windows with application to registration using mutual information. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **30**(10), 1841–1857.

Dufournaud, Y., Schmid, C., and Horaud, R. (2004). Image matching with scale adjustment. *Computer Vision and Image Understanding*, **93**(2), 175–194.

Eastman, R. D., Le Moigne, J., and Netanyahu, N. S. (2007). Research issues in image registration for remote sensing. In *Proceedings of the IEEE Computer Vision and Pattern Recognition Workshop on Image Registration and Fusion*, Minneapolis, MN, pp. 3233–3240.

Emery, W., Baldwin, D., and Matthews, D. (2003). Maximum cross correlation automatic satellite image navigation and attitude corrections for open-ocean image navigation. *IEEE Transactions on Geoscience and Remote Sensing*, **41**(1), 33–42.

Eugenio, F. and Marques, F. (2003). Automatic satellite image georeferencing using a contour-matching approach. *IEEE Transactions on Geoscience and Remote Sensing*, **41**(12), 2869–2880.

Faugeras, O. (1993). *Three-Dimensional Computer Vision*. Boston, MA: MIT Press.

Felicsimo, A. M., Cuartero, A., and Polo, M. E. (2006). Analysis of homogeneity and isotropy of spatial uncertainty by means of GPS kinematic check lines and circular statistics. In *Proceedings of the Seventh International Symposium on Spatial Accuracy Assessment in Natural Resources and Environmental Science*, Lisbon, Portugal, pp. 85–90.

Fitzpatrick, J., West, J. B., and Maurer, C. R. (1998). Predicting error in rigid-body point-based registration. *IEEE Transactions on Medical Imaging*, **17**(5), 694–702.

Flusser, J. and Suk, T. (1994). A moment-based approach to registration of images with affine geometric distortion. *IEEE Transactions on Geoscience and Remote Sensing*, **32**(2), 382–387.

Fonseca, L. M. G. and Manjunath, B. S. (1996). Registration techniques for multisensor remotely sensed imagery. *Photogrammetric Engineering & Remote Sensing*, **62**(9), 1049–1056.

Foroosh, H., Zerubia, J. B., and Berthod, M. (2002). Extension of phase correlation to subpixel registration. *IEEE Transactions on Image Processing*, **11**(3), 188–200.

Förstner, W. and Gülch, E. (1987). A fast operator for detection and precise location of distinct points, corners, and centers of circular features. In *Proceedings of the ISPRS Intermission Workshop on Fast Processing of Photogrammetric Data*, Interlaken, Switzerland, pp. 281–385.

Gavrilov, M., Indyk, P., Motwani, R., and Venkatasubramanian, S. (2004). Combinatorial and experimental methods for approximate point pattern matching. *Algorithmica*, **38**(1), 59–90.

Georgescu, B. and Meer, P. (2004). Point matching under large image deformations and illumination changes. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **26**(6), 674–688.

Goodrich, M. T., Mitchell, J. S. B., and Orletsky, M. W. (1999). Approximate geometric pattern matching under rigid motions. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **21**(4), 371–379.

Goshtasby, A. (1988). Registration of images with geometric distortions. *IEEE Transactions on Geoscience and Remote Sensing*, **26**(1), 60–64.

Goshtasby, A. (2005). *2-D and 3-D Image Registration for Medical, Remote Sensing, and Industrial Applications*. Hoboken, NJ: John Wiley and Sons.

Goshtasby, A. and Stockman, G. C. (1985). Point pattern matching using convex hull edges. *IEEE Transactions on Systems, Man, and Cybernetics*, **15**(5), 631–637.

Goshtasby, A., Stockman, G., and Page, C. (1986). A region-based approach to digital image registration with subpixel accuracy. *IEEE Transactions on Geoscience and Remote Sensing*, **24**(3), 330–399.

Govindu, V. and Shekhar, C. (1999). Alignment using distributions of local geometric properties. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **21**(10), 1031–1043.

Grodecki, J. and Lutes, J. (2005). IKONOS geometric calibrations. Technical report, Space Imaging.

Growe, S. and Tönjes, R. (1997). A knowledge based approach to automatic image registration. In *Proceedings of the International Conference on Image Processing*, Washington, DC, pp. 228–231.

Gruen, A. (1985). Adaptive least squares correlation: A powerful image matching technique. *South African Journal of Photogrammetry, Remote Sensing and Cartography*, **14**, 175–187.

Gupta, N. (2007). A VLSI architecture for image registration in real time. *IEEE Transactions on Very Large Scale Integration (VLSI) Systems*, **15**(9), 981–989.

Habib, A. F. and Alruzouq, R. I. (2004). Line-based modified iterated Hough transform for automatic registration of multi-source imagery. *The Photogrammetric Record*, **19**(105), 5–21.

Habib, A. F. and Al-Ruzouq, R. (2005). Semi-automatic registration of multi-source satellite imagery with varying geometric resolutions. *Photogrammetric Engineering & Remote Sensing*, **71**(3), 325–332.

Hagedoorn, M. and Veltkamp, R. C. (1999). Reliable and efficient pattern matching using an affine invariant metric. *International Journal of Computer Vision*, **31**(2–3), 103–115.

Harris, C. and Stephens, M. (1988). A combined corner and edge detector. In *Proceedings of the Fourth Alvey Vision Conference*, Manchester, UK, pp. 147–151.

Hasler, D., Sbaiz, L., Susstrunk, S., and Vetterli, M. (2003). Outlier modeling in image matching. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **25**(3), 301–315.

He, Y., Hamza, A. B. and Krim, H. (2003). A generalized divergence measure for robust image registration. *IEEE Transactions on Signal Processing*, **51**(5), 1211–1220.

Heffernan, P. J. and Schirra, S. (1994). Approximate decision algorithms for point set congruence. *Computational Geometry Theory and Applications*, **4**(3), 137–156.

Hong, G. and Zhang, Y. (2008). A comparative study on radiometric normalization using high resolution satellite images. *International Journal of Remote Sensing*, **29**(2), 425–438.

Hong, S. H., Jung, H. S., and Won, J. S. (2006). Extraction of ground control points (GCPs) from synthetic aperture radar images and SRTM DEM. *International Journal of Remote Sensing*, **27**(18), 3813–3829.

Hsieh, J.-W., Liao, H.-Y. M., Fan, K.-C., Ko, M.-T., and Hung, Y.-P. (1997). Image registration using a new edge-based approach. *Computer Vision and Image Understanding*,, **67**(2), 112–130.

Huseby, R. B., Halck, O. M., and Solberg, R. (2005). A model-based approach for geometrical correction of optical satellite images. *International Journal of Remote Sensing*, **26**(15), 3205–3223.

Huttenlocher, D. P. and Rucklidge, W. J. (1993). A multi-resolution technique for comparing images using the Hausdorff distance. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, New York, NY, pp. 705–706.

Huttenlocher, D. P., Klanderman, G. A., and Rucklige, W. J. (1993). Comparing images using the Hausdorff distance. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **15**(9), 850–863.

Huttenlocher, D. P., Kedem, K., and Sharir, M. (1993). The upper envelope of Voronoi surfaces and its applications. *Discrete and Computational Geometry*, **9**, 267–291.

Igbokwe, J. I. (1999). Geometrical processing of multi-sensoral multi-temporal satellite images for change detection studies. *International Journal of Remote Sensing*, **20**(6), 1141–1148.

Im, J., Rhee, J., Jensen, J. R., and Hodgson, M. E. (2007). An automated binary change detection model using a calibration approach. *Remote Sensing of Environment*, **106**(1), 89–105.

Inglada, J. and Giros, A. (2004). On the possibility of automatic multisensor image registration. *IEEE Transactions on Geoscience and Remote Sensing*, **41**(10), 2104–2120.

Inglada, J., Muron, V., Pichard, D., and Feuvrier, T. (2007). Analysis of artifacts in subpixel remote sensing image registration. *IEEE Transactions on Geoscience and Remote Sensing*, **45**(1), 254–264.

Irani, M. and Anandan, P. (1999). About direct methods. In *Proceedings of the IEEE ICCV Workshop on Vision Algorithms*, Corfu, Greece, pp. 267–277.

Irani, M. and Peleg, S. (1991). Improving resolution by image registration. *CVGIP: Graphical Models and Image Processing*, **53**(3), 231–239.

Iwasaki, A. and Fujisada, H. (2005). ASTER geometric performance. *IEEE Transactions on Geoscience and Remote Sensing*, **43**(12), 2700–2706.

Jenkinson, M. and Smith, S. (2001). A global optimisation method for robust affine registration of brain images. *Medical Image Analysis*, **5**, 142–156.

Jovanovic, V. M., Bull, M. A., Smyth, M. M., and Zong, J. (2002). MISR in-flight camera geometric model calibration and georectification performance. *IEEE Transactions on Geoscience and Remote Sensing*, **40**(7), 1512–1519.

Kaneko, S., Satohb, Y., and Igarashia, S. (2003). Using selective correlation coefficient for robust image registration. *Pattern Recognition*, **36**(5), 1165–1173.

Ke, Y. and Sukthankar, R. (2004). PCA-SIFT: A more distinctive representation for local image descriptors. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, Washington, DC, pp. 506–513.

Kedem, K. and Yarmovski, Y. (1996). Curve based stereo matching using the minimum Hausdorff distance. In *Proceedings of the Twelfth Annual ACM Symposium on Computational Geometry*, Philadelphia, PA, pp. C15–C18.

Keller, Y. and Averbuch, A. (2006). Multisensor image registration via implicit similarity. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **28**(5), 794–801.

Keller, Y., Shkolnisky, Y., and Averbuch, A. (2005). The angular difference function and its application to image registration. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **27**(9), 969–976.

Kelman, A., Sofka, M., and Stewart, C. V. (2007). Keypoint descriptors for matching across multiple image modalities and non-linear intensity variations. In *Proceedings of the IEEE Computer Vision and Pattern Recognition Workshop on Image Registration and Fusion*, Minneapolis, MN, pp. 1–7.

Kennedy, R. E. and Cohen, W. B. (2003). Automated designation of tie-points for image-to-image coregistration. *International Journal of Remote Sensing*, **24**(17), 3467–3490.

Kern, J. and Pattichis, M. (2007). Robust multispectral image registration using mutual-information models. *IEEE Transactions on Geoscience and Remote Sensing*, **45**(5), 1494–1505.

Kim, J. and Fessler, J. A. (2004). Intensity-based image registration using robust correlation coefficients. *IEEE Transactions on Medical Imaging*, **23**(11), 1430–1444.

Kirby, N. E., Cracknell, A. P., Monk, J. G. C., and Anderson, J. A. (2006). The automatic alignment and mosaic of video frames from the variable interference filter imaging spectrometer. *International Journal of Remote Sensing*, **27**(21), 4885–4898.

Klein, S., Pluim, J. P. W., Staring, M., and Viergever, M. A. (2009). Adaptive stochastic gradient descent optimisation for image registration. *International Journal of Computer Vision*, **81**(3), 227–239.

Klein, S., Staring, M., and Pluim, J. P. W. (2007). Evaluation of optimization methods for nonrigid medical image registration using mutual information and B-splines. *IEEE Transactions on Image Processing*, **16**(12), 2879–2890.

Knops, Z. F., Maintz, J. B. A., Viergever, M. A., and Pluim, J. P. W. (2006). Normalized mutual information based registration using *k*-means clustering and shading correction. *Medical Image Analysis*, **10**(3), 432–439.

Köhn, A., Drexl, J., Ritter, F., König, M., and Peitgen, H. O. (2006). GPU accelerated image registration in two and three dimensions. In *Proceedings of Bildverarbeitung für die Medizin 2006*. Hamburg: Springer Verlag, pp. 261–265.

Krupnik, A. (2003). Accuracy prediction for ortho-image generation. *The Photogrammetric Record*, **18**(101), 41–58.

Lazaridis, G. and Petrou, M. (2006). Image registration using the Walsh transform. *IEEE Transactions on Image Processing*, **15**(8), 2343–2357.

Le Moigne, J., Campbell, W., Cromp, R., Branch, A., and Center, N. (2002). An automated parallel image registration technique based on the correlation of wavelet features. *IEEE Transactions on Geoscience and Remote Sensing*, **40**(8), 1849–1864.

P1: SFK Trim: 174mm × 247mm Top: 0.553in Gutter: 0.747in
CUUK1136-03 cuuk1136/Le-Moigne ISBN: 978 0 521 51611 2 September 15, 2010 10:17

Le Moigne, J., Cole-Rhodes, A., Johnson, K., Morisette, J., Netanyahu, N. S., Eastman, R., Stone, H., and Zavorin, I. (2003). Earth science imagery registration. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium*, Toulouse, France, pp. 161–163.

Le Moigne, J., Morisette, J., Cole-Rhodes, A., Johnson, K., Netanyahu, N. S., Eastman, R., Stone, H., Zavorin, I., and Jain, P. (2004). A study of the sensitivity of automatic image registration algorithms to initial conditions. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium*, Anchorage, Alaska, pp. 1390–1393.

Le Moigne, J., Netanyahu, N. S., Masek, J. G., Mount, D., Goward, S., and Honzak, M. (2000). Geo-registration of Landsat data by robust matching of wavelet features. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium*, Honolulu, Hawaii, pp. 1610–1612.

Lee, D. S., Storey, J. C., Choate, M. J., and Hayes, R. W. (2004). Four years of Landsat-7 on-orbit geometric calibration and performance. *IEEE Transactions on Geoscience and Remote Sensing*, **42**(12), 2786–2795.

Leprince, S., Barbot, S., Ayoub, F., and Avouac, J. (2007). Automatic and precise orthorectification, coregistration, and subpixel correlation of satellite images, application to ground deformation measurements. *IEEE Transactions on Geoscience and Remote Sensing*, **45**(6), 1529–1558.

Lester, H. and Arridge, S. R. (1999). A survey of hierarchical non-linear medical image registration. *Pattern Recognition*, **32**(1), 129–149.

Li, H., Manjunath, B., and Mitra, S. (1995). Multisensor image fusion using the wavelet transform. *CVGIP: Graphical Models and Image Processing*, **57**(3), 235–245.

Li, Q., Wang, G., Liu, J., and Chen, S. (2009). Robust scale-invariant feature matching for remote sensing image registration. *IEEE Geoscience and Remote Sensing Letters*, **6**(2), 287–291.

Lowe, D. (1999). Object recognition from local scale-invariant features. In *Proceedings of the IEEE International Conference on Computer Vision*, Corfu, Greece, Vol. 2, pp. 1150–1157.

Lowe, D. G. (2004). Distinctive image features from scale-invariant keypoints. *International Journal of Computer Vision*, **20**(2), 91–110.

Lucas, B. D. and Kanade, T. (1981). An iterative image registration technique with an application to stereo vision. In *Proceedings of the International Joint Conference on Artificial Intelligence*, Vancouver, British Columbia, Canada, pp. 674–679.

Madani, H., Carr, J. L., and Schoeser, C. (2004). Image registration using AutoLand-mark. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium*, Anchorage, Alaska, pp. 3778–3781.

Maes, F., Collignon, A., Vandermeulen, D., Marchal, G., and Suetens, P. (1997). Multimodality image registration by maximization of mutual information. *IEEE Transactions on Medical Imaging*, **16**(2), 187–198.

Maes, F., Vandermeulen, D., and Suetens, P. (1999). Comparative evaluation of multiresolution optimization strategies for multimodality image registration by maximization of mutual information. *Medical Image Analysis*, **3**(4), 373–386.

Maintz, J. and Viergever, M. (1998). A survey of medical image registration. *Medical Image Analysis*, **2**(1), 1–36.

McGuire, M. and Stone, H. S. (2000). Techniques for multiresolution image registration in the presence of occlusions. *IEEE Transactions on Geoscience and Remote Sensing*, **38**(3), 1476–1479.

P1: SFK Trim: 174mm × 247mm Top: 0.553in Gutter: 0.747in
CUUK1136-03 cuuk1136/Le-Moigne ISBN: 978 0 521 51611 2 September 15, 2010 10:17

Mikolajczyk, K. and Schmid, C. (2004). Scale & affine invariant interest point detectors. *International Journal of Computer Vision*, **60**(1), 63–86.

Mikolajczyk, K. and Schmid, C. (2005). A performance evaluation of local descriptors. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **27**(10), 1615–1630.

Mikolajczyk, K., Tuytelaars, T., Schmid, C., and Zisserman, A. (2005). A comparison of affine region detectors. *International Journal of Computer Vision*, **65**(1–2), 43–72.

Modersitzki, J. (2004). *Numerical Methods for Image Registration*. Oxford: Oxford University Press.

Mount, D. M., Netanyahu, N. S., and Le Moigne, J. (1999). Efficient algorithms for robust feature matching. *Pattern Recognition*, **32**(1), 17–38.

Netanyahu, N. S., LeMoigne, J., and Masek, J. G. (2004). Georegistration of Landsat data via robust matching of multiresolution features. *IEEE Transactions on Geoscience and Remote Sensing*, **42**(7), 1586–1600.

Nies, H., Loffeld, O., Dönmez, B., Hammadi, A. B., and Wang, R. (2008). Image registration of TerraSAR-X data using different information measures. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium*, Boston, MA, pp. 419–422.

Orchard, J. (2007). Efficient least squares multimodal registration with a globally exhaustive alignment search. *IEEE Transactions on Image Processing*, **16**(10), 2526–2534.

Pan, C., Zhang, Z., Yan, H., Wu, G., and Ma, S. (2008). Multisource data registration based on NURBS description of contours. *International Journal of Remote Sensing*, **29**(2), 569–591.

Penney, G. P., Weese, J., Little, J. A., Desmedt, P., Hill, D. L. G., and Hawkes, D. J. (1998). A comparison of similarity measures for use in 2-D-3-D medical image registration. *IEEE Transactions on Medical Imaging*, **17**(4), 586–595.

Pluim, J. P. W., Maintz, J. B. A., and Viergever, M. A. (2000). Interpolation artefacts in mutual information based image registration. *Computer Vision and Image Understanding*, **77**(2), 211–232.

Pluim, J., Maintz, J., and Viergever, M. (2003). Mutual-information-based registration of medical images: A survey. *IEEE Transactions on Medical Imaging*, **22**(8), 986–1004.

Pluim, J. P., Maintz, J. B. A., and Viergever, M. A. (2004). *f*-Information measures in medical image registration. *IEEE Transactions on Medical Imaging*, **23**(12), 1506–1518.

Poe, G. A., Uliana, E. A., Gardiner, B. A., von Rentzell, T. E., and Kunkee, D. B. (2008). Geolocation error analysis of the special sensor microwave imager/sounder. *IEEE Transactions on Geoscience and Remote Sensing*, **46**(4), 913–922.

Radke, R. J., Andra, S., Al-Kofahi, O., and Roysam, B. (2005). Image change detection algorithms: A systematic survey. *IEEE Transactions on Image Processing*, **14**(3), 294–307.

Rajwade, A., Banerjee, A., and Rangarajan, A. (2009). Probability density estimation using isocontours and isosurfaces: Applications to information-theoretic image registration. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **31**(3), 475–491.

Reddy, B. and Chatterji, B. (1996). An FFT-based technique for translation, rotation and scale-invariant image registration. *IEEE Transactions on Image Processing*, **5**(8), 1266–1271.

P1: SFK Trim: 174mm × 247mm Top: 0.553in Gutter: 0.747in
CUUK1136-03 cuuk1136/Le-Moigne ISBN: 978 0 521 51611 2 September 15, 2010 10:17

Roche, A., Malandain, G., and Ayache, N. (2000). Unifying maximum likelihood approaches in medical image registration. Special Issue on 3D Imaging. *International Journal of Imaging Systems and Technology*, **11**(1), 71–80.

Rohde, G., Aldroubi, A., and Healy, D. (2008). Interpolation artifacts in sub-pixel image registration. *IEEE Transactions on Image Processing*, **18**(2), 333–345.

Roy, D. (2000). The impact of misregistration upon composited wide field of view satellite data and implications for change detection. *IEEE Transactions on Geoscience and Remote Sensing*, **38**(4), 2017–2032.

Salas, W. A., Boles, S. H., Frolking, S., Xiao, X., and Li, C. (2003). The perimeter/area ratio as an index of misregistration bias in land cover change estimates. *International Journal of Remote Sensing*, **24**(5), 1165–1170.

Salvado, O. and Wilson, D. L. (2007). Removal of local and biased global maxima in intensity-based registration. *Medical Image Analysis*, **11**(2), 183–196.

Salvi, J., Matabosch, C., Fofi, D., and Forest, J. (2006). A review of recent range image registration methods with accuracy evaluation. *Image and Vision Computing*, **25**(5), 578–596.

Schmid, C., Mohr, R., and Bauckhage, C. (2000). Evaluation of interest point detectors. *International Journal of Computer Vision*, **37**(2), 151–172.

Sen, M., Hemaraj, Y., Plishker, W., Shekhar, R., and Bhattacharyya, S. S. (2008). Model-based mapping of reconfigurable image registration on FPGA platforms. *Journal of Real-Time Image Processing*, **3**(3), 149–162.

Sester, M., Hild, H., and Fritsch, D. (1998). Definition of ground-control features for image registration using GIS-data. *International Archives of Photogrammetry and Remote Sensing*, **32/4**, 537–543.

Shams, R., Sadeghi, P., and Kennedy, R. A. (2007). Gradient intensity: A new mutual information based registration method. In *Proceedings of the IEEE Computer Vision and Pattern Recognition Workshop on Image Registration and Fusion*, Minneapolis, MN, pp. 3249–3256.

Shekarforoush, H., Berthod, M., and Zerubia, J. (1996). Subpixel image registration by estimating the polyphase decomposition of cross power spectrum. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, San Francisco, CA, pp. 532–537.

Skerl, D., Likar, B., and Pernus, F. (2006). A protocol for evaluation of similarity measures for rigid registration. *IEEE Transactions on Medical Imaging*, **25**(6), 779–791.

Stewart, C., Tsai, C., and Roysam, B. (2003). The dual-bootstrap iterative closest point algorithm with application to retinal image registration. *IEEE Transactions on Medical Imaging*, **22**(11), 1379–1394.

Stockman, G. C., Kopstein, S., and Benett, S. (1982). Matching images to models for registration and object detection via clustering. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **4**(3), 229–241.

Stone, H. S., Orchard, M., Chang, E. C., and Martucci, S. (2001). A fast direct Fourier-based algorithm for subpixel segistration of images. *IEEE Transactions on Geoscience and Remote Sensing*, **39**(10), 2235–2243.

Stone, H. S., Tao, B., and McGuire, M. (2003). Analysis of image registration noise due to rotationally dependent aliasing. *Journal of Visual Communication and Image Representation*, **14**, 114–135.

Sylvander, S., Henry, P., Bastien-Thiry, C., Meunier, F., and Fuster, D. (2000). VEGETATION geometrical image quality. *Société Française de Photogrammétrie et de Télédétection*, **159**, 59–65.

P1: SFK Trim: 174mm × 247mm Top: 0.553in Gutter: 0.747in
CUUK1136-03 cuuk1136/Le-Moigne ISBN: 978 0 521 51611 2 September 15, 2010 10:17

Theiler, J. P., Galbraith, A. E., Pope, P. A., Ramsey, K. A., and Szymanski, J. J. (2002). Automated coregistration of MTI spectral bands. In *Proceedings of the SPIE Conference on Algorithms and Technologies for Multispectral, Hyperspectral, and Ultraspectral Imagery VIII*, Orlando, FL, Vol. 4725, pp. 314–327.

Thévenaz, P. and Unser, M. (2000). Optimization of mutual information for multiresolution image registration. *IEEE Transactions on Image Processing*, **9**(12), 2083–2099.

Thévenaz, P., Bierlaire, M., and Unser, M. (2008). Halton sampling for image registration based on mutual information. *Sampling Theory in Signal and Image Processing*, **7**(2), 141–171.

Thévenaz, P., Ruttimann, U., and Unser, M. (1998). A pyramid approach to subpixel registration based on intensity. *IEEE Transactions on Image Processing*, **7**(1), 27–41.

Toutin, T. (2003). Error tracking in IKONOS geometric processing. *Photogrammetric Engineering & Remote Sensing*, **69**(1), 43–51.

Toutin, T. (2004). Review article: Geometric processing of remote sensing images: Models, algorithms and methods. *International Journal of Remote Sensing*, **25**(10), 1893–1924.

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

Tsao, J. (2003). Interpolation artifacts in multimodality image registration based on maximization of mutual information. *IEEE Transactions on Medical Imaging*, **22**(7), 854–864.

Tuytelaars, T. and Mikolajczyk, K. (2008). *Local Invariant Feature Detectors: A Survey*. Hanover, MA: Now Publishers, Inc.

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

Viola, P. A. and Wells, W. M. I. (1997). Alignment by maximization of mutual information. *International Journal of Computer Vision*, **24**(2), 137–154.

Wang, G., Gertner, G. Z., Shoufan, F., and Anderson, A. B. (2005). A methodology for spatial uncertainty analysis of remote sensing and GIS products. *Photogrammetric Engineering & Remote Sensing*, **71**(12), 1423–1432.

Wang, H. and Ellis, E. C. (2005a). Image misregistration error in change measurements. *Photogrammetric Engineering & Remote Sensing*, **71**(9), 1037–1044.

Wang, H. and Ellis, E. C. (2005b). Spatial accuracy of orthorectified IKONOS imagery and historical aerial photographs across five sites in China. *International Journal of Remote Sensing*, **26**(9), 1893–1911.

Wang, J., Di, K., and Li, R. (2005). Evaluation and improvement of geopositioning accuracy of IKONOS stereo imagery. *Journal of Surveying Engineering*, **131**(2), 35–42.

Wang, W.-H. and Chen, Y.-C. (1997). Image registration by control points pairing using the invariant properties of line segments. *Pattern Recognition Letters*, **18**(3), 269–281.

Wolfe, R. E., Nishihama, M., Fleiga, A. J., Kuyper, J. A., Roy, D. P., Storey, J. C., and Patt, F. S. (2002). Achieving sub-pixel geolocation accuracy in support of MODIS land science. *Remote Sensing of Environment*, **83**(1–2), 31–49.

Wong, A. and Clausi, D. A. (2007). ARRSI: Automatic registration of remote-sensing images. *IEEE Transactions on Geoscience and Remote Sensing*, **45**(5), 1483–1493.

Xia, M. and Liu, B. (2004). Image registration by "super-curves". *IEEE Transactions on Image Processing*, **13**(5), 720–732.

P1: SFK Trim: 174mm × 247mm Top: 0.553in Gutter: 0.747in
CUUK1136-03 cuuk1136/Le-Moigne ISBN: 978 0 521 51611 2 September 15, 2010 10:17

Xiong, X., Che, N., and Barnes, W. (2005). Terra MODIS on-orbit spatial characterization and performance. *IEEE Transactions on Geoscience and Remote Sensing*, **43**(2), 355–365.

Yam, S. and Davis, L. (1981). Image registration using generalized Hough transform. In *Proceedings of the IEEE Conference on Pattern Recognition and Image Processing* Dallas, Texas, pp. 525–533.

Yang, G., Stewart, C. V., Sofka, M., and Tsai, C. L. (2006). Automatic robust image registration system: Initialization, estimation, and decision. In *Proceedings of the Fourth IEEE International Conference on Computer Vision Systems*, New York, NY, pp. 23–31.

Yang, Z. and Cohen, F. S. (1999). Image registration and object recognition using affine invariants and convex hulls. *IEEE Transactions on Image Processing*, **8**(7), 934–947.

Yuan, Z.-M., Wu, F., and Zhuang, Y.-T. (2006). Multi-sensor image registration using multi-resolution shape analysis. *Journal of Zhejiang University SCIENCE A*, **7**(4), 549–555.

Zagorchev, L. and Goshtasby, A. (2006). A comparative study of transformation functions for nonrigid image registration. *IEEE Transactions on Image Processing*, **15**(3), 529–538.

Zavorin, I. and Le Moigne, J. (2005). Use of multiresolution wavelet feature pyramids for automatic registration of multisensor imagery. *IEEE Transactions on Image Processing*, **14**(6), 770–782.

Zhou, G. and Li, R. (2000). Accuracy evaluation of ground points from IKONOS high-resolution satellite imagery. *Photogrammetric Engineering & Remote Sensing*, **66**(3), 1103–1112.

Zitová, B. and Flusser, J. (2003). Image registration methods: A survey. *Image and Vision Computing*, **21**(11), 977–1000.

Zokai, S. and Wolberg, G. (2005). Image registration using log-polar mappings for recovery of large-scale similarity and projective transformations. *IEEE Transactions on Image Processing*, **14**(10), 1422–1434.