https://ntrs.nasa.gov/search.jsp?R=20180004558 2019-05-01T03:27:43+00:00Z

INTRODUCTION TO REMOTE SENSING IMAGE REGISTRATION

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ABSTRACT

For many applications, accurate and fast image registration of large amounts of multi-source data is the first necessary step before subsequent processing and integration. Image registration is defined by several steps and each step can be approached by various methods which all present diverse advantages and drawbacks depending on the type of data, the type of applications, the a priori information known about the data and the type of accuracy that is required. This paper will first present a general overview of remote sensing image registration and then will go over a few specific methods and their applications.

***Index Terms*—** Image registration, remote sensing, feature matching, alignment

1. INTRODUCTION

Earth science studies deal with issues such as climate change over multiple time scales, predicting crop production, monitoring land resources and understanding the impact of human activity on major Earth ecosystems. These issues are addressed by using global and repetitive measurements provided by a wide variety of satellite remote sensing systems. All these systems support multiple-time or simultaneous observations of the same Earth features by different sensors. Remote sensing systems provide global measurements that are not available using ground or even airborne sensors, and these measurements are often complemented by local or regional measurements. To reach the full benefit of such complementary measurements, all these datasets must be correlated and integrated; and the first step in this correlation and integration is image registration. The difficulty in registering these various data is that they usually have varying resolutions – spatial, spectral, radiometric, temporal and angular, they are acquired under different conditions – e.g., atmospheric, seasons, time of day, cloud coverage, and they cover features with various characteristics, e.g., natural features such as mountains or coastlines, or manmade features such as cities, bridges and roads. In addition to these various characteristics of the data, the application for which the data needs to be registered and the information known about the data adds a level of complexity to the registration process. When dealing with other types of registration such as medical registration, an image model is usually available and fiducial points can be used; for remote sensing image registration, it is much more difficult to have well-distributed ground control points in each scene that needs to be registered. It is even more difficult when dealing with other planets than the Earth. Finally, the size of the datasets often represents an additional challenge to the image registration problem. Therefore, many different methods for image registration have been developed that can deal with the multiple image characteristics and the multiple conditions and applications that need to be dealt with when performing remote sensing image registration [1]. This paper will present a general overview of remote sensing image registration, review some general registration frameworks, and will then describe a few representative algorithms.

2. WHAT IS IMAGE REGISTRATION

In the Earth remote sensing domain, the datasets are usually first processed using a navigation or model-based systematic correction; the model is based on characteristics related to orbit, attitude, platform/sensor, Earth model, etc. Image registration is then often called feature-based precision correction; it starts from the results of the systematic correction and is based on selected features extracted from the image data.

As a general definition, image registration is the process of aligning two or more images, or one or more images with another data source, e.g., a map containing vector data. Image registration can be described within a mathematical framework in which $I_1(x,y)$ and $I_2(x,y)$ are two images or one image and a map that need to be registered. The registration challenge is to find the mapping (f,g) which transforms I1 into I2 such that:

$$I_2(x,y) = g(I_1(f_x(x,y), f_y(x,y))) + n(x,y), \qquad (1)$$

in which *f* represents a spatial mapping, *g* is a radiometric mapping, and *n* is the noise term. Examples of spatial transformations can be a translation, a rigid or affine transformation, or even a projective, perspective of polynomial transformation. Examples of radiometric transformations are nearest neighbors, bilinear or cubic convolution transforms.

Another framework that describes image registration is the algorithmic framework first introduced by Brown [2], which includes the 4 main elements:

1. The *Search Space* of potential transformations, *f*

2. The *Feature Space* of information extracted from the 2 datasets
3. The *Similarity Metric* used to match the 2 sets of features
4. The *Search Strategy* that finds the optimal transformation.

To these 4 steps, we need to add the following ones:

5. The *Resampling Method* used to create the corrected image, if needed
6. The *Validation Method* by which the image registration algorithm is evaluated as accurate and reliable.

Many image registration surveys can be found in the literature, some general and some more focused on a specific domain such as remote sensing or medical imagery [1–5]. These surveys describe the many algorithms that have been designed in which various choices have been made and combined for elements 1 through 4/5. As described in [1], image registration algorithms are often broadly categorized as *area-based* or *feature-based*. Area-based methods match areas or regions without an explicit correspondence between points in the two images, while feature-based methods use a first step to extract "information-rich" features that are used for matching. But these 2 approaches are often combined in actual algorithms. So another way to group image registration considers the following categories:

- Manual Registration
- Correlation-Related Methods
- Fourier-Domain and Other Transform-Based Methods
- Mutual Information and Distribution-Based Approaches
- Feature-Point Methods
- Contour- and Region-Based Approaches.

In the remaining of this paper, we will focus on the 3 main components that are essential to design all these algorithms, namely: feature extraction, similarity metrics and matching strategies. Then, we will briefly describe a few representative algorithms and their applications to NASA data.

3. FEATURE EXTRACTION

Features can be either *gray levels*, either original or after enhancement; *salient points* such as those defined by an edge detector, a Fourier, Fourier-like, wavelet or wavelet-like transform, or a corner or interest point detector; or *contours, lines, shapes or regions*.

When features are chosen as gray levels, the values can be the original values of the images or they can be the values obtained after an enhancement operator such as an edge extractor, i.e., edge magnitudes, or a wavelet transformation, i.e., low-pass or high-pass subband magnitudes. In this case, the transformations f and g from Equation (1) are either found globally (e.g., using a Fast Fourier Transform [12] or a Fourier-Mellin Transform [13]) or can be found by combining local measurements using a similarity measure such as cross-correlation.

When using salient points, they can be matched either by finding point-to-point correspondences and then by computing the overall transformation from these point-to-point matchings; or by directly finding the transformation that provides the optimal matching between the two clouds of salient points. Apart from a general edge detector (e.g., Sobel, or Canny), other methods can be utilized. The first class of methods is linked to harmonic analysis, starting with short-time Fourier transforms, e.g., a Gabor transform, for which the window is a Gaussian function; more recently, discrete directional Gabor frames have also been proposed [6]. Wavelets, shearlets and wavelet-like representations such as the Simoncelli decomposition can also be utilized [7,8]; these representations allow to locally separate the pass and high-pass components of the signal and the highest values of these components can be used as salient points:

$$Wav(I)(a,b) = \frac{1}{\sqrt{a}} \iint_{-\infty}^{\infty} I(u,v).W(\frac{u\text{-}b_1}{a},\frac{v\text{-}b_2}{a})\, du\, dv \quad (2).$$

Salient points can also be obtained using an interest or a corner operator such as the Harris operator [9].

Other features, that take into account a larger amount of spatial information correspond to contours, lines or general shapes, can be extracted by methods such as line fitting, a simple or generalized Hough transform, or various region segmentation methods [1/Chapter 10]. Another approach, that was used for detecting animals such as flamingos, manmade features such as buildings and roads as well as natural features such as trees and planetary craters, uses a Marked Point Process (MPP) model [21]. An MPP is a framework in which probabilistic models are defined on configuration spaces consisting of an unknown number of parametric objects. A configuration consists of a set of marked points. Random parameters (called marks) are associated with each point. This framework allows to model geometric constraints about each or a group of objects. Each realization of an MPP represents a model for the possible spatial distribution of several objects in an image. Contours, shapes and objects are usually matched one-to-one and the transformation, f, is computed from these individual matchings.

Finally, methods like the Scale-Invariant Feature Transform (SIFT) and its variant, the Speeded Up Robust Features (SURF) method, detect and describe local features in images. The extracted features are invariant to uniform scaling, orientation and illumination changes; this allows for a direct matching of SIFT points between 2 images [10,11].

4. SIMILARITY METRICS

When matching any of the features described in Section 3, one wants to choose a similarity metrics that is the most appropriate to the algorithms and to the type of extracted features. These metrics include distances that will need to be

minimized and correlation-like measures that will need to be maximized. Some examples are:

- The Sum of Squared Distances (SSD), an L2 norm, over the region overlapping the 2 images:

$$SSD(x,y)=\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}\left[I_1(m,n)-I_2(m-x,n-y)\right]^2 \tag{3}$$

- The usual Cross-correlation:

$$I_1(x,y)\circ I_2(x,y)=\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}I_1(m,n)I_2(x+m,y+n) \tag{4}$$

  and the corresponding Normalized Cross-Correlation (NCC):

$$NCC_{I_1,I_2}(x,y)=\frac{\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}\left[I_1(m,n)-\bar{I}_1\right]\left[I_2(x+m,y+n)-\bar{I}_2\right]}{\sqrt{\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}\left[I_1(m,n)-\bar{I}_1\right]^2\cdot\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}\left[I_2(x+m,y+n)-\bar{I}_2\right]^2}} \tag{5}$$

- The Mutual Information (MI) measure, which maximizes the degree of statistical dependence between the images:

$$MI(I_1,I_2)=\sum_{g_1}\sum_{g_2}p_{I_1,I_2}(g_1,g_2)\cdot\log\left(\frac{p_{I_1,I_2}(g_1,g_2)}{p_{I_1}(g_1)\cdot p_{I_2}(g_2)}\right), \tag{6}$$

  and which also can be computed using histograms:

$$MI(I_1,I_2)=\frac{1}{M}\sum_{g_1}\sum_{g_2}h_{I_1,I_2}(g_1,g_2)\cdot\log\left(\frac{Mh_{I_1,I_2}(g_1,g_2)}{h_{I_1}(g_1)\cdot h_{I_2}(g_2)}\right) \tag{7}$$

  where M is the sum of all histogram entries, i.e., number of pixels (in overlapping subimages).

- Another similarity metrics that has been utilized in some algorithms is the Hausdorff or the partial Hausdorff distance defined by:

$$H_K(I_1,I_2)=K^{th}_{p_1\in I_1}\min_{p_2\in I_2}\operatorname{dist}(p_1,p_2), \tag{8}$$

  where $1\leq K\leq|I1|$.

- Finally, another less common metrics is the Discrete Gaussian Mismatch (DGM) where ws(a) denotes the weight of point a, and which is normalized between 0 and 1:

$$\mathrm{DGM}_\sigma(I_1,I_2)=1-\frac{\sum_{a\in I_1}w_\sigma(a)}{|I_1|}$$
$$w_\sigma(a)=\exp\left(-\frac{\operatorname{dist}(a,I_2)^2}{2\sigma^2}\right) \tag{9}$$

5. STRATEGIES FOR IMAGE MATCHING

Matching strategies are paired with the feature extraction and the similarity metrics to provide various registration algorithms, but as described in Section 3, not all matching strategies can be used for all feature extraction methods.

The most obvious matching strategy is the exhaustive search, i.e., looking at all potential transformations between the 2 datasets and select the transformation that yields the optimum similarity. Of course, this approach becomes exponential with the dimensionality of the transformation space and can rarely be applied in practice.

When dealing with gray level values, and when looking only for translations, the Fast Fourier Transform has been applied with great success by computing a phase correlation. The correlation can be computed efficiently in the Fourier domain by computing the inverse of the Fourier product:

$$F_1^*(u,v)\mathrm{F}_2(u,v) \tag{10}$$

This can also be extended to NCC, and finding small rotational and scale differences can be obtained by matching small moving chips [12]. If larger rotations and scales are involved, the images can first be transformed into the Fourier-Mellin domain which is translation-invariant, and represents rotation and scale change as translations in the angular and radius coordinates [13].

Still, the most popular strategy for matching features seems to be optimization. It can be applied to gray levels as well as to individual features, globally on the large images or locally on sub-images. There are various types of optimization techniques, the simplest being the steepest gradient descent; others are based on the Levenberg-Marquart algorithm [7,14] or on a stochastic gradient [15]. This last method, although computationally more expensive, avoids to actually compute the gradient and instead provides an estimate; this can be of interest with more complicated similarity metrics such as the mutual information.

Another strategy involves Robust Feature Matching (RFM) using an efficient subdivision and pruning of the transformation space and has been described in [16].
When dealing with contours and shapes, other approaches are being considered; for example, local geometric distributions described in [1], and genetic algorithms used to register binary shapes [17].

More recently, neural networks have also been considered to perform image registration [18]. Although counter-intuitive for a well-defined problem such as registration, the mapping of the image registration problem to a neural network framework is adapted to the rise of new types of hardware such as quantum and cognitive computing [19]. Although it has not yet reached its full potential, it offers great promise for registering large amounts of data very quickly.

At the same time, matching strategies also involve looking at the image either globally or performing local independent registrations over small sub-images that are then either stitched at the edges between multiple tiles of the image or recombined to compute a global transformation. Other approaches look at multi-resolution approaches, such as wavelets or shearlets, with or without decimation, looking at a coarser transformation space in the first iterations, and progressively refining the accuracy of the transformation while reducing the search space in the later iterations. Similar approaches can be taken by using other types of image representations such as quadtrees [20].

6. A FEW IMAGE REGISTRATION ALGORITHMS

In this section, a few algorithms combining previously described feature extraction methods, similarity metrics and

matching strategies, are presented as illustrations of the previous sections.

6.1. Wavelet and Wavelet-Like Based Algorithms

Our team developed several algorithms based on wavelet or wavelet-like features, using several similarity metrics such as L2 Norm and mutual information, and with a multi-resolution optimization matching strategy following the structure of the wavelet decomposition. Results, presented in refs [1,7,8], show the strengths and weaknesses of various features depending on the initial conditions of the optimization process; some features will provide a higher registration accuracy when starting close to the solution, while some other features will provide a better robustness when the optimization starts further from the solution. Results presented in [8] also show that for very textured images, regular features (even SIFT) do not yield high registration accuracy while features taking rotation into account (such as shearlets) can quickly provide an approximate solution. Mutual information, although computationally more expensive, provides a sharper peak and therefore a better accuracy for the final solution.

6.2. Marked Point Process Based Algorithms

More recently, we performed work using MPP models for crater detection and we used these extracted craters as the features to perform planetary data registration. Hausdorff distance and Mutual Information were used as similarity metrics; both a multi-resolution approach and a region-based approach were used as search strategies, and a genetic algorithm provided the feature matching. Results are presented in [22] and [23].

7. CONCLUSION

This paper presented a brief introduction to remote sensing image registration and its main components, namely feature extraction, similarity metrics and matching strategies. These components need to be adapted to the variety of data to register, the many data acquisition methods and conditions as well as the many applications registration is needed for. Current and future work will involve a systematic assessment of these various components that will help future users choose the most appropriate image registration algorithm for their data and its applications.

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