Automatic Registration of Inter-band and Inter-sensor Images using Robust Complex Wavelet Feature Representations

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Abstract

A robust method for registering inter-band and inter-sensor remote sensing images has been designed and implemented. The proposed method introduces noise-resilient and contrast invariant control point detection and control point matching schemes based on robust complex wavelet feature representations. Furthermore, an iterative refinement scheme is introduced for achieving improved control point pair localization and mapping function estimation between the images being registered. The registration accuracy of the proposed method was demonstrated on the registration of multi-spectral optical and synthetic aperture radar (SAR) images. The proposed method achieves better registration accuracy when compared with the state-of-the-art M-SSD and ARRSI registration algorithms.

1 Introduction

A challenging problem in remote sensing image analysis is image registration, where remote sensing images acquired under different conditions are aligned with each other. Applications of image registration in remote sensing image analysis include change analysis, building detection [1], and canopy modeling [2]. The common approach to the registration of remote sensing images is to manually select ground control points from the images and estimate the mapping function based on these ground control points. Given the large amount of remote sensing images being received on a daily basis, this manual selection of ground control points is very time consuming. Therefore, an automated approach to image registration is desired to help reduce processing time.

Various methods have been proposed for the purpose of automatic image registration of remote sensing images. These can be divided into intensity-based methods [3, 4], frequency-based methods [5], and feature-based methods [6, 7]. A particularly difficult scenario faced in automatic image registration in the context of remote sensing is the registration of remote sensing images acquired from different spectral bands or different sensors (i.e., optical, SAR, LIDAR). This is due to the fact that different spectrums and sensors capture different characteristics from the same scene. Therefore, the same image content is represented by different intensity values, making it difficult to compare images in a direct manner based on intensity values. Feature-based methods, in which image similarity is evaluated based on extracted features (e.g., edges, corners, roads, buildings, etc.), have shown to be particularly promising in registering inter-band and inter-sensing images and have been adopted in recent research work in remote sensing image registration [7]. Current feature-based image registration techniques suffer from the following drawbacks:

1. **Noise sensitivity**: Sensor noise can have a significant impact on the control point detection and matching processes. While efforts have been made to reduce noise sensitivity [7], current methods are still highly sensitive to situations characterized by high levels of noise and irrelevant image details.

2. **Contrast sensitivity**: Remote sensing images often exhibit global and local contrast conditions that can cause the same image content to possess different intensity values. While techniques have been used to address contrast variation issues [7], the effectiveness of these techniques drop significantly in the presence of high noise levels.

3. **Control point location inaccuracies**: An assumption made in current methods is that the locations of matched control points are exactly the same in their respective images. However, this is often not true due to inaccuracies during the control point detection process. Location offsets between matched control points can result in inaccurate mapping function estimates and thereby reducing registration accuracy.

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The main contribution of this paper is an automatic registration algorithm designed to address the problems associated with the existing methods in the context of inter-band and inter-sensor remote sensing images. Control point detecting and matching methods based on robust complex wavelet feature representations are introduced to address issues associated with noise and contrast sensitivity. Control point location inaccuracies are dealt with using an iterative control point refinement method.

2 Control Point Detection and Matching using Robust Complex Wavelet Feature Representations

The underlying goal of image registration is to align one or more images (denoted as sensed images) to a base image (denoted as the reference image). The first steps in automatic image registration are to identify and match control points from sensed images to the reference image. This process is particularly difficult when dealing with inter-sensor and inter-band images for a number of reasons. Due to intensity differences between images from different spectrum bands and sensing modalities, identifying equivalent control points between the sensed images and reference image is a difficult task. Also, it is difficult to evaluate the similarity between image content with different intensity mappings. Contrast non-uniformity and noise further complicate the situation. Feature-based methods address issues associated with inter-band and inter-sensor image registration by extract features that can be compared directly between the sensed images and the reference image. An effective approach to control point detection and matching is that proposed by Wong et al. [7], which utilizes complex wavelet phase moments as features. The main advantage of this approach is that it not only captures the structural characteristics that are independent of pixel intensities, but it is also robust to global and local contrast variations. However, the effectiveness of the approach used by Wong et al. noticeably decreases in the presence of noise and irrelevant image details. To address this issue, the proposed method introduces control point detection and matching schemes that utilize robust complex wavelet feature representations obtained based on the iterative complex wavelet phase coherence moment estimation method [8].

The proposed control point detection and matching schemes can be described as follows. Given an image I_0, the amplitude and phase A_0 and ϕ_0 are obtained using complex wavelets (e.g., Gabor wavelets and dual-tree complex wavelets [9]) and an initial estimate of the local phase coherence ρ_0 is obtained. At each subsequent iteration k, the minimum and maximum complex wavelet phase coherence moments φ_k and υ_k are determined using ρ_{k-1}. A new image estimate I_k is determined based on υ_k using the moment-adaptive bilateral estimation scheme proposed in [10]:

$$I_k(x,y) = \frac{\sum\limits_{\psi} w\big(x,y,\psi,\upsilon_k\left(x,y\right)\big) I_{k-1}\left(\psi\right)}{\sum\limits_{\psi} w\big(x,y,\psi,\upsilon_k(x,y)\big)} \tag{1}$$

where w is an estimation weighting function defined as the product of moment-adaptive spatial and amplitudinal weighing functions w_s and w_a over a local neighborhood ψ:

$$\begin{aligned} &w\big(x,y,\psi,\upsilon_k(x,y)\big) = \\ &w_a\big(x,y,\psi,\upsilon_k(x,y)\big) \cdot w_s\big(x,y,\psi,\upsilon_k(x,y)\big) \end{aligned} \tag{2}$$

The weighting functions w_s and w_a are defined in [10]. The local phase coherence for the next iteration ρ_{k+1} can then be estimated using I_k. The robust complex wavelet feature representations used in the proposed method consists of the final maximum and moment complex wavelet phase coherence moment estimates after n iterations (where n represents the number of iterations at convergence):

$$\zeta = \{\varphi_n, \upsilon_n\} \tag{3}$$

During the control point detection process, non-maximum suppression and thresholding are performed on the minimum complex wavelet phase coherence moments φ_n. Control points are selected as the strongest n points in the image that are local maxima of φ_n within a fixed radius. The position of the control points are then refined on a sub-pixel level using a quadratic estimation scheme based on neighboring pixels. During the control point matching process, the similarity between control points extracted from the sensed images and the reference image is determined based on the normalized cross-correlation between the maximum complex wavelet phase coherence moments υ_n:

$$\kappa(p_r, p_s) = \frac{\sum\limits_{x}\sum\limits_{y} \left(\upsilon_n^{p_r}(x,y)\upsilon_n^{p_s}(x,y)\right)}{\sqrt{\sum\limits_{x}\sum\limits_{y} (\upsilon_n^{p_r}(x,y))^2 (\upsilon_n^{p_s}(x,y))^2}} \tag{4}$$

where p_r and p_s are control points from the reference image and a sensed image respectively, and $\upsilon_n^{p_s}(x,y)$ and $\upsilon_n^{p_r}(x,y)$ are the maximum complex wavelet phase coherence moments at (x,y) with a region centered around p_s and p_r respectively.

3 Iterative Control Point Pair Refinement

After identifying matching control point pairs, it is necessary to estimate the mapping function that aligns sensed images with the reference image. This is typically done using least squares solvers such as the normalized direct linear transformation (DLT) algorithm [12]. The accuracy of the estimated mapping function is heavily dependent two main factors: i) the accuracy of the matching process, and ii) the accuracy of the locations of corresponding control point pairs. While the problem of matching accuracy has been tackled by researchers using outlier rejection schemes such as the Random Sample Consensus (RANSAC) algorithm [11], little attention has been focused on the problem of control point pair accuracy. Current control point refinement techniques adjust the location of control points independent of other control points as performed in Section 2. This can lead to control point pair offset errors that can reduce the accuracy of the estimated mapping function. To address this issue, the proposed method introduces an iterative control point pair refinement scheme that adjusts the location of control points in sensed images relative to their corresponding control points in the reference image based on robust complex wavelet feature representations.

The proposed control point pair refinement scheme can be described as follows. First, the Maximum Distance Sample Consensus (MDSAC) algorithm [7] is used to prune erroneous control point pairs from the set of control point pairs found during the control point matching process. For each remaining control point pair, the location of the control point in the sensed image is adjusted iteratively to maximize the normalized cross-correlation between the maximum complex wavelet phase coherence moments around the control point in the sensed image p_s and the control point in the reference image p_r. The control point refinement problem can be expressed as an optimization problem:

$$\hat{p}_s = \arg\max_{p_s} \left(\kappa\left(p_r, p_s\right)\right) \tag{5}$$

where $\hat{p}_s$ is the refined location of the control point in the sensed image. In the proposed method, the local optimization scheme used is an iterative solver based on sequential quadratic programming (SQP) [13]. The current location of the control point in the sensed image is used as the initial estimate for $\hat{p}_s$ and is re-estimated iteratively on a sub-pixel basis until convergence is reached. This set of refined control points, now largely free of outliers and localization inaccuracies, is used to estimate the final mapping function that aligns the sensed image with the reference image.

4 Experimental Results

The proposed method was tested using the same inter-sensor and inter-band test sets described in [7], which consists of four LANDSAT 4/5-7 inter-band test sets from the U.S. Geological Survey (USGS) Global Visualization Viewer project and one LANDSAT 7-SAR inter-sensor test set derived from the Spaceborne Imaging Radar-C/X-Band Synthetic Aperture Radar (SIR-C/X-SAR) project. To evaluate the registration accuracy of the proposed algorithm, the root mean squared error (RMSE) is computed for a set of 10 ground-truth control point pairs. The state-of-the-art multi-modal registration algorithms proposed in [4] and [7] were used for comparison.

The registration accuracy results are shown in Table 1. The proposed method outperforms the other registration methods under evaluation in terms of RMSE in all test cases. An example of the registration achieved for two of the test cases is shown in Figure 1 and Figure 2. By visual inspection, the registration appears to be accurate in both test cases. These results demonstrate the effectiveness of the proposed algorithm in registering inter-band and inter-sensor images.

Table 1. Registration accuracy

Test Set	RMSE[1] (pixels)		
	M-SSD [4]	**ARRSI [7]**	**Proposed**
INTER1	55.6633	3.7815	2.6837
INTER2	2.3664	1.6426	1.2880
INTER3	6.5345	1.2184	1.2013
INTER4	3.7815	2.7906	1.9380
INTER5	-[2]	8.5854	3.7326

1: RMSE is computed as the average of 5 test trials given the randomness in the registration process.
2: Fails to register images within RMSE < 100.

5 Conclusions

In this paper, we introduced a novel method for registration inter-band and inter-sensor remote sensing images based on robust complex wavelet feature representations. It is designed to be highly robust to contrast variations, noise, and irrelevant image details that can result in reduced registration accuracy. An iterative control point pair refinement method was presented to improve control point pair localization such that better mapping function estimates can be achieved. Experimental results indicate superior registration accuracy when compared to existing methods. Future work involves investigating alternative similarity functions as

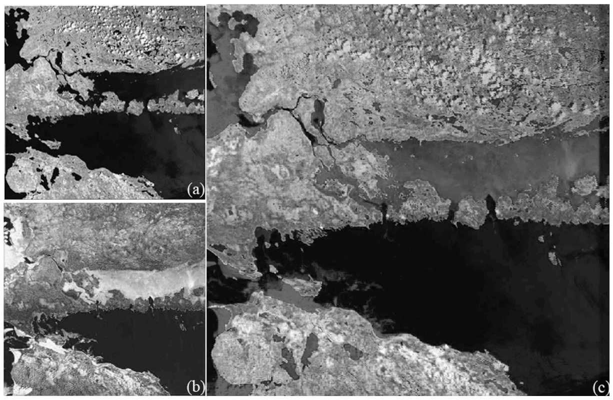

Figure 1. Image registration from INTER1: a) reference image; b) sensed image; c) aligned images

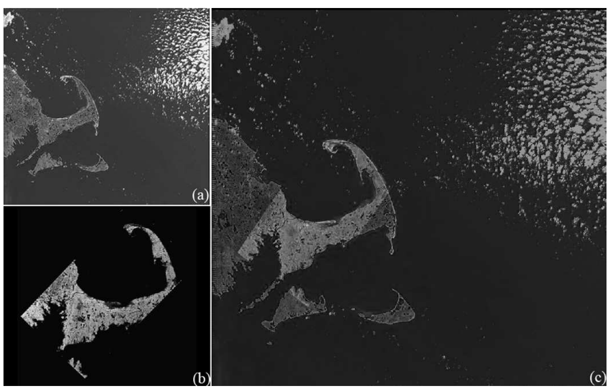

Figure 2. Image registration from INTER5: a) reference image; b) sensed image; c) aligned images

well as alternative features to complement the robust complex wavelet feature representations used in the proposed method.

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