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Poor textural image tie point matching via graph theory

Xiuxiao Yuan [a,b], Shiyu Chen [a], Wei Yuan [a,c,*], Yang Cai [a]

[a] School of Remote Sensing and Information Engineering, Wuhan University, Wuhan 430079, China
[b] Collaborative Innovation Center for Geospatial Technology, Wuhan 430079, China
[c] Center for Spatial Information Science, University of Tokyo, Kashiwa 277-8568, Japan

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ABSTRACT

Feature matching aims to find corresponding points to serve as tie points between images. Robust matching is still a challenging task when input images are characterized by low contrast or contain repetitive patterns, occlusions, or homogeneous textures. In this paper, a novel feature matching algorithm based on graph theory is proposed. This algorithm integrates both geometric and radiometric constraints into an edge-weighted (EW) affinity tensor. Tie points are then obtained by high-order graph matching. Four pairs of poor textural images covering forests, deserts, bare lands, and urban areas are tested. For comparison, three state-of-the-art matching techniques, namely, scale-invariant feature transform (SIFT), speeded up robust features (SURF), and features from accelerated segment test (FAST), are also used. The experimental results show that the matching recall obtained by SIFT, SURF, and FAST varies from 0 to 35% in different types of poor textures. However, through the integration of both geometry and radiometry and the EW strategy, the recall obtained by the proposed algorithm is better than 50% in all four image pairs. The better matching recall improves the number of correct matches, dispersion, and positional accuracy.

1. Introduction

Tie point matching is a fundamental task in computer vision, pattern recognition, photogrammetry, and remote sensing. This task aims to find sparse feature correspondences in overlapping areas (Hartmann et al., 2016). Radiometric information is sufficient to match fine tie points when images have distinctive and abundant textures. However, remote sensing images typically have poor textures. Examples of environments that tend to generate poor textures are forests, bare lands, deserts, and urban areas. Forest images have repetitive patterns on a small scale, bare land images have homogenous textures, desert images have few textures, and urban images are occluded and discontinuous. From the perspective of local appearance, a "poor texture" denotes low contrast or nonlinear gray variation between two conjugated regions. Thus, using radiometric information alone in matching poor textural images is inadequate, and manual interventions are sometimes necessary. Such interventions will hinder the automation of tie point matching.

Existing matching algorithms can be divided into two categories. The first category refers to algorithms based on radiometric information, such as normalized cross correlation (Gonzalez and Woods, 1992), SIFT (Lowe, 2004), and distinctive order-based self-similarity (Sedaghat and Ebadi, 2015). These matching algorithms are effective when image textures are fine and distinctive (Krystian and Cordelia, 2005). The second category comprises matching algorithms that integrate radiometric and geometric information; these algorithms include semi-global matching (Heiko, 2008), patch-based multi-view stereos (Furukawa and Ponce, 2007), and multi-photo geometrically constrained matching (Zhang and Armin, 2006). These matching algorithms take advantage of predetermined geometric information, which functions as a supplementary matching constraint. The aim of the integration methods is to first decompose the matching problem into several subproblems under certain constraints and then obtain the matching result via an iterative process until all subproblems converge on the same solution or on similar solutions.

Only a few studies have been conducted on poor textural image tie point matching. Wu et al. (2012) integrated point and line features to acquire a 3D dense point cloud based on prior knowledge of camera geometry for multiple views. Zickler and Efros (2007) used principal component analysis SIFT (PCA-SIFT, Ke and Sukthankar, 2004) for object detection in partially occluded

* Corresponding author.
E-mail addresses: yuanxx@whu.edu.cn (X. Yuan), csy_hy@whu.edu.cn (S. Chen), miloyw@whu.edu.cn, miloyw@iis.u-tokyo.ac.jp (W. Yuan), Y.Tsai@whu.edu.cn (Y. Cai).

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low-contrast textures and achieved satisfactory results. Another commonly used algorithm in poor textural image matching is line feature matching, such as line intersection context feature (Kim and Lee, 2010), mean–standard deviation line descriptor (Wang et al., 2009), line segment matching (LSM, Bay et al., 2005), and LSM with a homographic constraint (Sun et al., 2015). These algorithms detect line features in rich structured images, and line features are then matched by line descriptors. However, line features are not always presented in remote sensing images.

Poor textural image matching remains a challenging task in the following aspects. First, textural homogeneity is generally represented by low local image contrast; hence, radiometry-based matching methods are disturbed by noises. Radiometry-based tie point matching algorithms, such as SIFT, SURF (Bay et al., 2006), and FAST (Mair et al., 2010), cannot extract desirable tie points either in terms of the number of correct matches or in positional accuracy. Second, textural repetition is represented by regular pixel-wise recurrence, and feature descriptors are not distinctive. Thus, these approaches are prone to produce incorrect matches. Third, textural occlusion typically leads to local geometric distortion and nonlinear density changes in shaded regions. Moreover, the radiometric feature descriptor distance between two conjugate regions is insufficiently close. The overall issues in poor textural tie point matching are deficient correct matches, mismatching, and numerous incorrect matches.

The main idea of graph-based (Chung, 1997) tie point matching algorithms considers image features as graph nodes. The feature matching problem is then transformed into a node correspondence problem, which can be solved via graph matching (Livi and Rizzi, 2013). Geometric constraints mainly used for graph matching can be divided into three types: unitary constraints (or point-wise constraints), edge constraints (or pair-wise constraints), and triplet constraints (or triangle constraints). Among these three types, pair-wise constraints are the most extensively concerned. These constraints encode the relationship between two point sets in graph edges. Pair-wise constraints are typically embedded in graph matching algorithms, such as spectral graph matching (Leordeanu and Hebert, 2005), graduated assignment (Gold and Rangarajan, 1996), probabilistic graph matching (Egozi et al., 2013), and balanced graph matching (Schölkopf et al., 2006). Triplet constraints can use the triangle information of graphs. They are locally affine-invariant constraints while pair-wise constraints are only distance-invariant. High-order graph matching (HOGM, Duchenne et al., 2011) is a representative triplet constraint algorithm. All the aforementioned graph matching algorithms yield poor matching results when numerous outliers are present. Cho et al. (2014) proposed a max-pooling strategy to address outliers but used only pair-wise constraints. Torresani et al. (2008) applied a graph matching algorithm in image feature correspondences; however, the results were not affine-invariant because only pair-wise constraints were used. Thus, a novel matching algorithm based on a high-order affinity tensor is proposed in this study, and the relations of the two graphs are encoded in the tensor. Compared with traditional radiometric–geometric integration algorithms, the proposed algorithm has threefold significant differences. (1) Geometric information plays a role similar to radiometric information rather than acting as a supplementary constraint in matching. (2) The matching result is globally optimal in both geometry and radiometry. When SIFT matching is used as an example, the nearest/next distance ratio (NNDR) is an effective measure for matching; however, it is only globally optimal in radiometry. (3) The matching algorithm uses an edge-weighted affinity tensor which makes the matching robust to outliers.

The rest of this paper is organized as follows. Section 2 focuses on the methodology of graph matching and the proposed EW affinity tensor. Section 3 provides a detailed implementation flow of the matching method and the experimental results. Section 4 draws the conclusions of this study.

2. Methodology

This section proposes an EW-HOGM method to address the poor textural image matching problem. Section 2.1 presents the concepts of HOGM. Section 2.2 introduces the proposed EW-HOGM. Section 2.3 describes the experimental results of the synthetic data. Section 2.4 provides a theatrical analysis of the computational complexity.

2.1. HOGM

Image tie point matching finds correspondences between two sets of features; this process can be defined as a graph matching problem. As shown in Fig. 1, five pairs of image features are extracted from the source and target images. Image features can be regarded as the nodes of graphs, and feature characters, such as locations and gray levels, are the attributes of the nodes. The relationship between two features, such as angles and distances, can be considered the edges of graphs. The matching problem of two image feature sets is a node matching problem of the two graphs. Hence, the tie point matching problem is transformed into a graph matching problem.

Given two image feature sets P and Q, and their corresponding graphs GP and GQ. If nodes $V_i \in G_P$ and $V_{i'} \in G_Q$ are assignments, then $f_i \in P$ and $f_{i'} \in Q$ are tie points, and vice versa. The graph matching problem can be formulated as

$$C \triangleq \{c_{ii'}\}_1^n = \{(V_i, V_{i'})\}_1^n, \quad n \leqslant \min(n_P, n_Q) \tag{1}$$

where C is an assignment set; nP and nQ are the feature numbers of two feature sets; i and i' are the labels of nodes V_i and $V_{i'}$, which represent the node indices in this paper; and $c_{ii'}$ is an assignment element of C, and it indicates V_i corresponds to $V_{i'}$.

The relationship (i.e., correspondences) of the graph nodes can also be depicted by assignment matrix $\boldsymbol{Z}^* \in \{0,1\}^{n_P \times n_Q}$, where $z^*_{ii'} = 1$ implies that V_i corresponds to $V_{i'}$ and $z^*_{ii'} = 0$ implies that V_i is not matched to any node in GQ. As shown in Fig. 2, the graph matching problem can be divided into three types based on their constraint forms: first-order, second-order, and high-order (third or higher) graph matching problems.

The first-order graph matching problem is established on a unitary affinity matrix $\mathbf{A} \in IR^{n_P \times n_Q}$ with

$$a_{ii'} = \Omega_1(c_{ii'}) = \exp\left(-\frac{1}{\varepsilon^2}(\|\mathbf{f}_i - \mathbf{f}_{i'}\|_2)^2\right) \tag{2}$$

where $a_{ii'}$ is the point-wise similarity of nodes V_i and $V_{i'}$; $\Omega_1(.)$ denotes the point-wise similarity measure (e.g., Euclidean distances of SIFT descriptors); $\|.\|_2$ represents the length of a vector; $\mathbf{f}_i$ and $\mathbf{f}_{i'}$ are the attributes of nodes V_i and $V_{i'}$, respectively, i.e., they are the radiometric descriptors of f_i and $f_{i'}$.

The first-order graph matching problem finds the optimal solution for the following objective function:

$$\begin{aligned} &\boldsymbol{z}^* = \arg\max_{\boldsymbol{z}}(\boldsymbol{z}^{\mathrm{T}}\boldsymbol{a}) \in \{0,1\}^{n_P \times n_Q} \\ &s.t. \quad \boldsymbol{Z1} \leqslant \boldsymbol{1},\ \boldsymbol{Z}^{\mathrm{T}}\boldsymbol{1} \leqslant \boldsymbol{1} \end{aligned} \tag{3}$$

where $\mathbf{a} \in IR^{n_P n_Q}$ is the row-wise vectorization of matrix $\boldsymbol{A}$, $\boldsymbol{1}$ denotes a vector that all elements are one; $\boldsymbol{Z}$ is a soft assignment matrix located in the continuous vector space, and $\boldsymbol{Z}^* \in \{0,1\}^{n_P \times n_Q}$ is a hard assignment matrix. Thus, an additional process is required to discretize $\boldsymbol{Z}$ into a binary matrix, and the commonly selected method for discretization is the greedy algorithm (shown in Algorithm 1, Leordeanu and Hebert, 2005).