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Identification of multi-scale corresponding object-set pairs between two polygon datasets with hierarchical co-clustering

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ABSTRACT

In this paper, we propose a means of finding multi-scale corresponding object-set pairs between two polygon datasets by means of hierarchical co-clustering. This method converts the intersection-ratio-based similarities of two objects from two datasets, one from each dataset, into the objects' proximity in a geometric space using a Laplacian-graph embedding technique. In this space, the method finds hierarchical object clusters by means of agglomerative hierarchical clustering and separates each cluster into object-set pairs according to the datasets to which the objects belong. These pairs are evaluated with a matching criterion to find geometrically corresponding object-set pairs. We applied the proposed method to the segmentation result of a composite image with 6 NDVI images and a forest inventory map. Regardless of the different origins of the datasets, the proposed method can find geometrically corresponding object-set pairs which represent hierarchical distinctive forest areas.

1. Introduction

The integration of a remotely sensed image and a thematic vector map can offer an improved understanding of the spectral information of land cover and the attribute information of map objects (Blaschke et al., 2000). The image is dissected into homogeneous image objects through segmentation, after which corresponding image and map object pairs are found and their information is analyzed. However, the performance during the segmentation process is often characterized by over-segmentation or under-segmentation (Hussain et al., 2013), causing a single image object to correspond to a map object-set or vice-versa and sometimes an image object-set to correspond to a map object-set. Thus, it is necessary to find not only 1:1 corresponding but also 1:N, M:1 and M:N pairs between image and map object datasets.

There have been many attempts to find such pairs. In studies of context-based image retrieval, the correspondence problem is treated as an assignment or transportation problem. Li et al. (2000) proposed the integrated region matching method which uses the "most similar, highest priority" rule to assign a region of one image to a region set of another image. This method is similar to obtaining a basic feasible solution of a transportation problem using a minimum-cost method. Greenspan et al. (2000) and Jing et al. (2004) proposed methods based on the Earth Mover's Distance in which the costs of shipping from the sources to the destinations are measured by the similarities between the regions of each image. In map conflation studies, Bel Hadj Ali (2000) and Sester et al. (2007) proposed a graph-connectivity-based method in which the objects and their intersection relationships between the datasets are represented as nodes and edges of a bipartite graph, respectively. The nodes connected to the edges are identified, after which each of the node clusters is divided into two object-sets according to the datasets to which the objects belong. These object-set pairs are evaluated with a matching criterion. However, the pairs are obtained by a simple object-intersection analysis. Thus, a clustering result can be vulnerable to spatial uncertainty as regards the position or shape of the objects. To address this problem, Huh et al. (2011) applied an indeterminate boundary model for polygon objects. The authors connected the nodes when the interior regions of the objects intersect each other, making their method robust to the above uncertainty problem.

Although these studies yielded successful results, further improvements are necessary to find multi-scale corresponding object-set pairs. In studies involving geospatial-object-based image analysis (Arbiol et al., 2006; Blaschke, 2010; Hay et al., 2005), semantically significant object-sets of each dataset are found at different analysis scales. Thus, it is difficult to estimate the optimal

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scales for datasets with which semantically significant corresponding object-set pairs are obtained. This problem can be solved by finding multi-scale corresponding object-sets between the hierarchical object-set structures of each dataset, where a smaller corresponding object-set pair can be a sub-part of a larger one. Compared to this structure, the aforementioned studies obtain corresponding object-set pairs between flat object-set structures, which partition each dataset into mutually exclusive object-sets. Therefore, once an object is used for a corresponding object-set pair, the object is no longer used to make super- or sub-object-set pairs of the pair, even if the super- or sub-object-set pairs would be more appropriate for the purpose of a certain integration case.

To address the above problem, this paper proposes a new method to find multi-scale corresponding polygon object-set pairs by means of hierarchical co-clustering. The goal is to obtain hierarchical super- and sub-object-sets within each polygon object dataset containing an image and a map along with their hierarchical corresponding structure. The basic idea of the proposed method begins with a graph-connectivity-based analysis (Bel Hadj Ali, 2000; Huh et al., 2011; Sester et al., 2007). This method modifies the graph-connectivity-based analysis into a hierarchical co-clustering analysis on a weighted bipartite graph whose nodes and edge weights denote the objects and the intersection-ratio-based similarities of two objects from two datasets, one from each dataset, respectively. This method uses two assumptions. First, if two objects, one from each dataset, intersect with a higher degree of similarity, they would have higher priority to make a corresponding object-set pair between the two datasets. Second, if two objects within a dataset intersect common objects in another dataset with higher degrees of similarity, they would have higher priority to make an object-set within their dataset. Considering these priority levels as a proximity metric in a geometric space, we treat all objects of both datasets as a collective whole object-set and then cluster these objects according to the metric by means of agglomerative hierarchical clustering. However, the priorities are only measured for the intersecting objects between datasets. Thus, these locally measured priorities can be presented as the edge weights of a bipartite graph data. Conventional mathematical tools or analysis methods which are suitable for feature vector data cannot be easily applied to graph data. To address this problem, a Laplacian-graph embedding technique is applied to embed individual objects into the coordinates in a low-dimensional geometric feature space. Thus, the Euclidean distance between two embedded objects is inversely proportional to their similarity (Yan et al., 2007). In this embedding space, the proposed method finds the hierarchical object clusters with an agglomerative hierarchical clustering method and divides each cluster into two object-sets according to the datasets to which the objects belong. Then, these object-set pairs from the object clusters are evaluated with a matching criterion to find the geometrically corresponding object-set pairs between the two datasets. Because the above object clusters in the embedding space have a hierarchical structure, the clusters can present hierarchical multi-scale corresponding object-set pairs.

The remainder of this paper is organized as follows. In the next section, the proposed method is presented in detailed steps. Then, in Section 3, the proposed method is applied to find the multi-scale corresponding polygon object-sets between the segmentation result of a composite NDVI (normalized difference vegetation index) acquired by the Landsat7 ETM+ and a forest inventory map. Finally, the conclusion is given in Section 4.

2. The proposed method

In this study, there are several interrelated key concepts. These are object, object-set, object cluster, node, object-set pair, and the geometrically corresponding object-set pair. The object in this case refers to a polygon object of either dataset. The object-set refers to the set of objects in a single dataset, such as {1, 2} or {13, 14} in Fig. 1(a). The object cluster indicates for a coordinate cluster in an embedding space such as C_i, or C_j in Fig. 1(c). These object clusters are obtained by agglomerative hierarchical clustering, which presents the clustering result in a dendrogram, as shown in Fig. 1(d), and each node of the dendrogram represents an object cluster. The object-set pair is obtained by dividing an object cluster into two object-sets according to the datasets to which the objects belong. For example, an object-set pair of {1, 2}:{13, 14} between dataset A and dataset B is obtained from object cluster C_i. Dendrogram nodes with the exception of leaf nodes at the bottom have right and left sub-branches of nodes. In Fig. 1(d), the node of C_i is one of the sub-nodes of C_j, and object cluster C_j contains object cluster C_i, as shown in Fig. 1(c). Thus, the proposed method presents super- and sub-geometrically corresponding object-set pairs and enables multi-scale analysis of corresponding object-set pairs between two datasets. However, some object clusters, such as C_k and C_m in Fig. 1(d), do not present geometrically corresponding object-set pairs. C_k is composed of objects from only dataset B, and the object-set pair {7}:{15}from C_m present a geometrically non-corresponding object-set pair. Thus, a matching criterion that evaluates the pair's geometric similarity is applied to find geometrically corresponding object-set pairs among object-set pairs.

The process of the proposed method has four steps, as shown in Fig. 1. First, the object-intersection-ratio-based similarities between two datasets are measured, after which they are represented as a weighted bipartite graph (step 01). Because conventional clustering methods cannot be directly applied to graph data, a graph-embedding technique is applied to obtain the coordinates of each object in a low-dimensional embedding space, where the proximities between the embedding coordinates are proportional to the object similarity levels (step 02). With these coordinates, agglomerative hierarchical clustering presents the hierarchical object clusters as nodes in a dendrogram (step 03). Among the all object-set pairs from the object cluster, geometrically corresponding object-set pairs are found with a matching criterion (step 04).

Details of the steps are as follows.

2.1. Intersection ratio-based similarity between two objects

Generally, spatial objects are geo-referenced so that the ratio of the intersection area to the union area is an effective similarity metric to find the corresponding objects (Bel Hadj Ali, 2000; Huh et al., 2011). However, the method cannot explain the part-whole relationship of two objects, which is necessary to find corresponding object-set pairs (Li and Goodchild, 2011; Min et al., 2007). Thus, the ratio of the intersection area to the area of a smaller object is used, as this ratio adequately explains whether a small object is a part of a large one. However, an intersection area and its ratio between small objects are vulnerable to positional discrepancies between two datasets (Huh et al., 2011). These discrepancies cannot be removed by a conventional map registration process with several control point pairs because the discrepancies are randomly generated by the segmentation errors of image objects and spatial uncertainties of the map objects. Thus, the ratios of small objects are less reliable than those of large objects. Moreover, a group of small objects can bridge neighboring distinctive corresponding object-set pairs when the group of one dataset locates along the boundary between the adjacent object-sets in another dataset and have similar intersection ratios to the object-sets. This is because small objects have same level of importance as large objects. To alleviate these problems, we multiply the intersection area by the ratio, as shown in Eq. (1), because a larger intersection area