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.

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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
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 \( C_i \), 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 \( C_i \) and \( C_m \) in Fig. 1(d), do not present geometrically corresponding object-set pairs. \( C_i \) 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
between two objects increases the reliability of their intersection relationship and ratio.
\[
W_{ij} = \frac{\text{Area}(a_i \cap b_j)}{\min\{\text{Area}(a_i), \text{Area}(b_j)\}} \times \text{Area}(a_i \cap b_j)
\]
(1)
where \(a_i\) and \(b_j\) are the polygon objects in datasets \(A\) and \(B\), respectively.

For the two polygon object datasets shown in Fig. 1(a), the similarity \(w_{ij}\) of objects \(a_i\) and \(b_j\) is represented by an entry in the symmetric similarity matrix \(W \in \mathbb{R}^{n_A \times n_B}\). Here, \(n = n_A + n_B\) is the sum of the object numbers in datasets \(A\) (\(n_A\)) and \(B\) (\(n_B\)). Each row and column of \(W\) corresponds to an object in the two datasets as shown in Fig. 1(b).

2.2. K-dimensional graph embedding of similarity measures

K-dimensional graph embedding represents the coordinates of the objects as rows in a \(n \times k\) matrix \(X = [x_1, \ldots, x_k]\). Here, \(k\) denotes the dimensionality of the embedding space. Each entry of a column vector \(x_d = (x_{d1}, \ldots, x_{dn})^T\), \(1 \leq d \leq k\), represents the coordinates of the embedded objects in the \(d\)th dimensional space. Thus, the \(i\)th row of \(X\), \(x^{(i)} = (x_{1(i)}, \ldots, x_{n(i)})\), is the \(k\)-dimensional coordinates of object \(o_i\). These coordinates can be obtained by minimizing the objective function shown in Eq. (2) (Belkin and Niyogi, 2003; Yan et al., 2007). This minimization makes the objects with higher similarity closer to each other, while those with lower similarity are farther from each other. Thus, the similarities between objects are preserved as the proximities between the embedding coordinates of the objects. Alternatively, this minimization problem can be represented by a matrix manipulation scheme, as shown in the form of the term on the right in Eq. (2) (Belkin and Niyogi, 2003; Yan et al., 2007).

\[
\frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \|x^{(i)} - x^{(j)}\|^2 w_{ij} = \text{trace}(X^T LX)
\]
(2)
where \(w_{ij}\) denotes the similarity between object \(o_i\) and object \(o_j\), and \(x^{(i)}\) and \(x^{(j)}\) are the \(k\)-dimensional coordinates of object \(o_i\) and object \(o_j\) respectively. Additionally, \(L\) is the graph Laplacian, which is defined by Eq. (3).

\[
L = D - W
\]
(3)
where \(D\) is a diagonal matrix whose diagonal entries are obtained by summing the similarities to object \(o_i\) as \(d_{ii} = \sum_j w_{ij}\).

Sameh and Wisniewski (1982) proved that if a graph is undirected and connected graph, the solution of the above matrix trace minimization problem is obtained by the \(k\) eigenvectors that correspond to the smallest positive eigenvalues. Thus, the solution is obtained as the matrix \(X = [x_1, \ldots, x_k]\), \(1 \leq d \leq k\), where \(x_d\) is an eigenvector corresponding to eigenvalue \(\lambda_d\), as shown in Eq. (4), when \(0 = \lambda_0 < \lambda_1 \leq \cdots \leq \lambda_k\) (Belkin and Niyogi, 2003).

\[
Lx_0 = \lambda_0 Dx_0
\]
\[
Lx_1 = \lambda_1 Dx_1
\]
\[
\ldots
\]
\[
Lx_k = \lambda_k Dx_k
\]
(4)
To apply the above method, it is necessary to determine the optimal dimensionality \(k\). Dhillon (2001) proposed Eq. (5) to obtain \(k\),
assuming that each eigenvector has the necessary information to partition the objects into at least two clusters. In the case of Fig. 1, both datasets have eight objects; thus, the optimal dimensionality is determined to be 3. With three eigenvectors \( x_1, x_2, x_3 \) and their entries, the embedding coordinates of the objects can be obtained as shown in Fig. 1(c).

\[
k = \lceil \log_2(\min(n_A, n_B)) \rceil
\]

where \( \lceil \cdot \rceil \) is a ceiling function which presents the smallest integer larger than an input real number.

The graph embedding technique in this study assumes a connected graph (Belkin and Niyogi, 2003; Yan et al., 2007), which means that all objects should have at least one path of similarities larger than 0 connected to another object. Otherwise, it is necessary to apply the proposed method separately for each connected graph.

2.3. Agglomerative hierarchical clustering of objects in the embedding space

We choose an agglomerative hierarchical clustering method to find multi-scale corresponding object-set pairs, as shown in Fig. 2. Starting from \( n \) polygon objects in \( O \) (line 03) as the initial object clusters (line 04), the clustering method searches for the two most similar object clusters (line 08). Then, it merges the two clusters into one super-object cluster (line 09) and produces new clustering by removing the two object clusters and inserting the super-object cluster (line 10). This super-object cluster is inserted into a set of object clusters (line 09). These steps are repeated until all objects are merged into a single cluster. Finally, all object clusters in \( M \) are evaluated to find geometrically corresponding object-set pairs. This evaluation step is explained in the following section.

To apply the above clustering method, it is necessary to define the object-set dissimilarity \( D(C_a, C_b) \). Compared to the dissimilarity of two objects measured by the Euclidean distance between their embedding coordinates, there are several measures for object clusters, such as the single-link measure, the complete-link measure and the average-link measure, as shown in Fig. 3 (Theodoridis and Koutroumbas, 2009). The single-link measure defines the dissimilarity as the minimum distance among all the object distances between two object clusters, as shown in Eq. (6). Thus, the method tends to find elongated clusters. Meanwhile, the complete-link measure defines the dissimilarity as the maximum distance, as shown in Eq. (7), and it tends to find tight clusters. The average-link measure is a compromise between the other two measures, as shown in Eq. (8). It tends to find an intermediate structure between loosely bound single-link clusters and tightly bound complete-link clusters (Cho et al., 2009). Considering the above properties, we choose the average-link measure with which to measure the cluster dissimilarity.

\[
D^{(s)}(C_a, C_b) = \min_{a_i \in C_a, a_j \in C_b} d(a_i, a_j)
\]

\[
D^{(c)}(C_a, C_b) = \max_{a_i \in C_a, a_j \in C_b} d(a_i, a_j)
\]

\[
D^{(a)}(C_a, C_b) = \frac{1}{|C_a||C_b|} \sum_{a_i \in C_a} \sum_{a_j \in C_b} d(a_i, a_j)
\]

where \( d(a_i, a_j) \) denotes the dissimilarity of objects \( a_i, a_j \) measured by the Euclidean distance between the objects’ embedding coordinates \( x_i \) and \( x_j \); and \( |C| \) is the number of objects in cluster \( C \).

2.4. Evaluation of object-set pairs with a matching criterion

Given an object cluster, it is divided into two object-sets according to the datasets to which the objects belong, presenting an object-set pair. Then, a matching criterion is applied to confirm it as a geometrically corresponding object-set pair. If two object-sets represent the same real-world entity, they would have similar geometric features, such as the position or shape. Among various matching criteria, the intersection ratio of Eq. (9) is chosen as the criterion. In general, two datasets have inevitable positional discrepancy which is caused by spatial uncertainty. This discrepancy can distort an intersection area of two object-sets. To address this problem, the object-sets are aligned with their centroid coordinates, as shown in Eq. (9).

\[
S(A', B') = \frac{M(A') \cap f^C(M(B'))}{M(A') \cup f^C(M(B'))}
\]

In this equation, \( A' = \{a_1', \ldots, a_l'\} \) and \( B' = \{b_1', \ldots, b_m'\} \) are two object-sets from the \( c \) th object cluster. \( M \) and \( f^C \) specify the function that combines the disjointed polygon objects into one super-object and the function that aligns the mass centroids of two object-sets \( A' \) and \( B' \), respectively.

The object-set pairs are searched in the bottom-up merging order, as shown in Fig. 4. If the similarity threshold for a matching criterion is set to 0.9, the object-set pair of \{1, 2\};\{13, 14\} is chosen as a geometrically corresponding object-set pair, while

![Fig. 3. Cluster dissimilarity measures: single-link measure, average-link measure and complete-link measure.](image-url)
the remaining pairs of \{2\};\{14\} and \{1\};\{13\} are rejected because their similarities are less than the threshold.

The above corresponding object-set pairs are obtained through agglomerative hierarchical clustering, which repeatedly merges two closest object clusters into one super-object cluster. However, this process occasionally presents redundant corresponding object-set pairs whose object components are nearly identical except for one or a few small objects, as shown in Fig. 5. This problem occurs because some pre-matured object-set pairs satisfy the matching criteria of Eq. (9). To avoid this problem, the similarity levels between the corresponding object-set pairs are measured by Eq. (10); the pairs whose similarities are larger than 0.95 are grouped. Then, the final corresponding object-set pairs are determined as the pairs which have the largest similarity in Eq. (9) for each group.

\[
S(A^{c1}; B^{c1}, A^{c2}; B^{c2}) = \max \left( \frac{M(A^{c1}) \cap M(A^{c2})}{M(A^{c1}) \cup M(A^{c2})} \frac{M(B^{c1}) \cap M(B^{c2})}{M(B^{c1}) \cup M(B^{c2})} \right)
\]

(10)

3. Experiment and discussion

3.1. Experimental dataset

We applied the proposed method to two polygon object datasets. The first one (Fig. 6(a)) is obtained by the segmentation of a composite NDVI image acquired at six different times. The Feature Extraction module of the ENVI Ex software package was used to segment the composite image. The second one (Fig. 6(b)) is obtained by the spatial joining of three forest inventory maps of the forest type, age and density. Because the test site is a protective district for nature conservation, it can be assumed that the vegetation land cover is barely changed as compared to when the datasets were obtained; thus, the image objects derived from the segmentation of the composite image reflect the diverse characteristics of forests, as represented by the forest maps. This means that there would be geometrically corresponding object-set pairs between two datasets. The details of these datasets and descriptions of the map object symbols are presented in Tables 1 and 2, respectively.

Before the proposed method was applied to the datasets, fifteen geometrically corresponding object-set pairs were manually found to determine the threshold of the matching criterion. The mean and standard deviation of the pairs’ similarity levels were 0.79 and 0.05, respectively. Thus, the threshold was set to the lower bound of the 95% confidence interval, 0.70.

3.2. Result and discussion

By applying the graph embedding process described in Section 2.2 to the object similarities of two datasets in Fig. 6, the embedding coordinates of each object are obtained. These object coordinates are shown in Fig. 7 with scatter plots showing the first, fourth and seventh dimensional coordinates in Fig. 7(a); the second, fifth and eighth dimensional coordinates in Fig. 7(b); and the third and sixth dimensional coordinates in Fig. 7(c). In this embedding space, the objects that are coherently connected to each other with high levels of similarity constitute clusters. In contrast, the outlier objects’ coordinates are far from the clusters.

A hierarchical arrangement of object clusters obtained from the agglomerative hierarchical clustering method can be represented by a dendrogram, as shown in Fig. 8, where the bottom row of nodes represents individual objects of two datasets, and the remaining nodes correspond to the object clusters in M in Fig. 2.

A matching criterion with a similarity threshold of 0.70 was applied for the object-set pairs derived from the object clusters, showing 92 corresponding object-set pairs. Among these 92 pairs, 19 pairs had an M:1 correspondence pair, indicating a pair of many image objects matched to a single map object, as shown in Fig. 9. In addition, the remaining 73 pairs were M:N correspondence pairs, which means a pair of many image objects matched to many map objects, as shown in Figs. 11 and 12. Meanwhile, in this experiment, there were 1:1 or 1:N correspondence pairs.

An accuracy assessment was carried out for the 19 M:1 pairs. To prepare the reference pairs, we manually found 21 M:1 correspondence pairs whose similarity levels were greater than 0.70. Compared to the reference pairs, five pairs were false ones and seven pairs of the 21 reference pairs were not detected. This result was
assessed by precision and recall, as shown in Table 3. The precision measures the ratio of correctly detected pairs over the total number of detected pairs, and the recall measures the ratio of correctly detected pairs over the total number of reference pairs. However, four false pairs were caused by omitted or committed small image objects, as shown in Fig. 10. This problem originated...
from the similarity of Eq. (1), which considers the absolute sizes of the objects. As a result, the similarities of small objects, though their intersection ratios may be significantly large, are underestimated and ignored in the Laplacian graph embedding process, as the embedding process is a type of data-reduction technique, such as principal-component-analysis or multidimensional-scaling-analysis, and does not sufficiently account for those small similarities in the data-reduction process. Thus, the coordinates of such small objects would not be properly projected in the embedding space. However, the omitted or committed objects above could be easily found by a simple intersection analysis between a map object and image objects. After this post-process, precision and recall increased to 0.95 and 0.86, respectively.

If a corresponding object-set pair represents the same real-world entity or phenomenon, the two object-sets would have similar geometric features; however, the opposite is not true. Thus, not all corresponding object-set pairs represent meaningful distinctive forest areas. Simply put, it can be assumed that the map objects which constitute a corresponding object-set pair have similar phenological characteristics. The image objects are derived from the boundaries between the image areas where the phenological characteristics change, while the map objects are derived from the boundaries between the forest areas where interpretation according to the data model of the forest inventory map changes. Because the corresponding object-set pair represents a forest area which shares its boundary with the two boundaries described above, the map objects which constitute a corresponding pair would have similar phenological characteristics compared to their neighboring map objects which do not constitute the corresponding object-set pair. In Fig. 9, map objects with specific forest species such as Korean pine (PK), larch (PL) and pitch pine (PR) with high age and density classes are found as M:1 correspondence pairs. This can be useful information for a further image analysis because forest areas with the above attributes would be more accurately identified from a composite NDVI image.

The small- and middle-scale M:N correspondence pairs shown in Fig. 11 present the attribute-similarities of the forest inventory map’s data model, as the attributes of the object-sets in this corresponding object-set pair can be assumed to be similar in terms of their phenological characteristics. In Fig. 11(b), the detected pairs of A1, A2, A3 and A4 have forest types similar to that of a conifer forest. While the remaining examples with different forest types have a common characteristic in which the ages and densities of conifer forests are not higher than those of broadleaf or mixed forests. This indicates that a young and sparse conifer forest has phenological characteristics similar to an old and dense broadleaf forest. Thus, these two types of forest areas would not be accurately distinguished with a composite NDVI image, and a different type of remotely sensed data is therefore necessary.

Large-scale M:N correspondence pairs do not present explicit information because the attributes of the map object-set of each pair do not have meaningful common characteristics. Compared with the digital elevation model of the test site, some boundaries between the pairs in Fig. 12(a) and (b) are related to the ridges or valleys in Fig. 12(c). This shows that the landscape of the test site affects forest growth related to the forest type, age, density and phenological characteristic. However, further analysis is required to understand the meaning of this.

As the sizes of M:N correspondence pairs increase, the similarities in Eq. (9) tend to exceed 0.90. However, this did not present

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**Fig. 8.** Agglomerative hierarchical clustering dendrogram the average-link measure.

**Fig. 9.** Detected M:1 correspondence pairs between dataset A (a) and dataset B (b).

**Fig. 10.** Omitted and committed small image objects.
meaningful information, as these large-scale pairs were obtained by merging previously found corresponding object-set pairs and coincidently shared boundaries of image objects and map objects.

4. Conclusion

In this paper, we proposed a method to find multi-scale corresponding object-sets between two polygon datasets using an agglomerative hierarchical clustering process on a Laplacian-graph embedding space of the intersection-ratio-based object similarities. The method consists of four steps: (1) a measurement of the object-intersection-ratio-based similarities and representation of the similarities in a weighted graph, (2) the Laplacian-graph embedding of the graph to obtain the object coordinates so that the proximities between the coordinates are proportional to the aforementioned object similarities, (3) an agglomerative hierarchical clustering analysis of the coordinates to find the candidate corresponding object-set pairs, and (4) an evaluation of the candidates with a matching criterion to confirm the final matching pairs.

We applied the proposed method to the two polygon object datasets. One was obtained by the segmentation of a composite NDVI image acquired in six different times, and the other was obtained by the spatial join of the forest type, age and density map. For M:1 correspondence pairs of an image object-set to a single map object, precision and recall were 0.95 and 0.86, respectively, after an object-intersection based post-process. These pairs represent an improved understanding of some forest areas in terms of their phenological characteristics. Moreover, landscape characteristics related to ridges and valleys were derived from large-scale M:N correspondence pairs.

In the process of data integration between remotely sensed data and GIS data, a 1:1 corresponding object pair is a notably restrictive assumption. Moreover, a specific integration process may be needed to find specific scaled object-sets and their corresponding pairs. The proposed method can find such object-sets in a hierarchical matching structure. This is the originality and contribution of this study. A further improvement is also necessary. The proposed method only considers the intersection ratio-based
similarity between two datasets. However, the attribute-similarities of neighboring objects within a dataset can be inserted into the diagonal parts of an edge weight matrix (Fig. 1(b)) to present geometrically corresponding object-set pairs whose object-set in each dataset has homogenous attributes. Given a proper weight model for geometric and semantic similarities, these similarities can be combined in the embedding process, after which more meaningful information can be derived from the matching results.

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