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A framework of region-based spatial relations for non-overlapping features and its application in object based image analysis

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Abstract

Object based image analysis (OBIA) is an approach increasingly used in classifying high spatial resolution remote sensing images. Object based image classifiers first segment an image into objects (or image segments), and then classify these objects based on their attributes and spatial relations. Numerous algorithms exist for the first step of the OBIA process, i.e. image segmentation. However, less research has been conducted on the object classification part of OBIA, in particular the spatial relations between objects that are commonly used to construct rules for classifying image objects and refining classification results. In this paper, we establish a context where objects are areal (not points or lines) and non-overlapping (we call this "single-valued" space), and propose a framework of binary spatial relations between segmented objects to aid in object classification. In this framework, scale-dependent "line-like objects" and "point-like objects" are identified from areal objects based on their shapes. Generally, *disjoint* and *meet* are the only two possible topological relations between two non-overlapping areal objects. However, a number of quasi-topological relations can be defined when the shapes of the objects involved are considered. Some of these relations are fuzzy and thus quantitatively defined. In addition, we define the concepts of line-like objects (e.g. roads) and point-like objects (e.g. wells), and develop the relations between two line-like objects or two point-like objects. For completeness, cardinal direction relations and distance relations are also introduced in the proposed context. Finally, we implement the framework to extract roads and moving vehicles from an aerial photo. The promising results suggest that our methods can be a valuable tool in defining rules for object based image analysis.
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Keywords: Region-based spatial relations; Single-valued space; Object based image analysis

1. Introduction

Object based image analysis (frequently called OBIA) is an approach to classifying high resolution remotely sensed imagery that is currently seeing increased use due to the proliferation of imagery with small pixel sizes, such as those provided by digitized aerial photographs and the IKONOS and QuickBird satellites. Conventional pixel-based methods, while useful in classifying coarse-scale remotely sensed imagery, are less suitable for classifying high resolution images (Toll, 1984; Xia, 1996; Guo et al., 2007).

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Generally, an object based image classifier includes two major steps: first an image is segmented into similar image objects (or segments) and then the objects are classified based on attributes of and interrelations between segmented objects (Benz et al., 2004; Blaschke and Hay, 2001; Guo et al., 2007; Hay et al., 2003). The process typically transforms a raster image format into a vector one: most segments are operationally analyzed as polygons. The segmentation step is not new, and has been widely studied especially in the field of pattern recognition (such as Lobo (1997), Li et al. (1999), Cheng et al. (2001), Hay et al. (2003), Wang et al. (2005), to name but a few). However, less research has been conducted on the classification part of the process.

Three levels or scales of features can be derived from a segmented image and used for image classification (Aksoy et al., 2003). Level 1 features are properties of a single image segment, such as area, perimeter, shape index, and a range of texture measurements (Herold et al., 2003), that can be considered to classify the segment. For example, Guo et al. (2007) used these features to more accurately distinguish between dead crowns and bare ground in an oak forest. Level 2 features focus on spatial relations between two objects, such as containment, proximity, and adjacency; these can also be used to classify an image segment or refine the classification result. For example, if an image segment that is spectrally similar to vegetation occurs next to an image segment that is classified to be a house, the first segment is likely to be a lawn. Level 3 features are spatial patterns in which more than two objects are involved and could be used to aid in classifying segmented objects. For example, in some ex-urban developments, houses can be distributed rather than regular, while in some suburban areas, houses can be regularly arrayed. These inter-segment relations can be used to more successfully classify the houses.

Many methods are available to extract level 1 features (e.g. a polygon's perimeter and area etc. are routinely quantified in GIS software), and less formal methods exist for retrieving and utilizing the spatial relations between segmented objects (level 2 features) and spatial patterns among multiple objects (level 3 features). A few models have been developed to represent topological relations in raster data Egenhofer and Sharma (1993), Winter and Frank (2000), and Winter and Bittner (2002) even introduces topological relations between vague regions. However, these models are not suitable for OBIA since the objects in OBIA are non-overlapping. Additionally, although areal objects are extracted based on raster imagery in OBIA, the spatial relations among those areal objects should be defined and analyzed more successfully with a vector representation because the vector data model is more capable of handling geometrical shapes and topological relations of areal objects than is the raster model; these are crucial characteristics for extracting level 2 features.

In this study, we focus on defining level 2 features from segmented images, i.e. the spatial relations between image segments. Note that although level 3 features are not the primary goal of this research, information gathered from level 2 features is important for defining and extracting level 3 features (Aksoy et al., 2003). The remainder of the paper is organized as follows: first, we review relevant spatial relation studies and discuss some unique characteristics of segmented images; we then propose a framework of region based spatial relations for segmented images; and finally, we implement the proposed framework to extract roads and moving vehicles from an aerial photo as a case study.

1.1. Spatial relations

Spatial relations between objects continue to be an important topic in geographic information sciences. A formal description of the possible relations between spatial entities is essential in order to perform spatial queries, and to answer the questions about topology (e.g. adjacency, containment or inclusion), proximity and direction that are fundamental to all geographic analyses. Spatial relations are typically organized into three categories: topological relations, distance relations, and relations of cardinal direction (Renz, 2002; Yao and Thill, 2006), and there is considerably more literature dealing with the first of these aspects of spatial relations — topology (Egenhofer, 1991; McDonnell and Kemp, 1995).

Topological relations are those that are invariant under topological transformations, and are preserved under translation, rotation and scaling. Egenhofer and Franzosa (1991) proposed the first formalization of spatial relations between two spatial entities as a 4-intersection model (4-IM) (Egenhofer and Franzosa, 1991); and later this model was expanded to a 9-intersection model (9-IM) (Egenhofer and Herring, 1991; Egenhofer and Sharma, 1993). In this paper, we only provide a brief introduction to the intersection model (for more detailed information, please see articles by Egenhofer and colleagues). For a two-dimensional object X certain characteristics can be defined: the earlier 4-intersection model considered the object's interior (denoted by $I(X)$) and its boundary (denoted by $B(X)$) (Fig. 1); the 9-intersection model adds

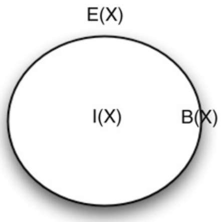


Fig. 1. Object characteristics: (a) Interior (I) and boundary (B); (b) and exterior (E) of an areal object.

consideration of its exterior (denoted by $E(X)$) (Fig. 1). The topological relations between two objects, for example X and Y, can be represented by a 2×2 (in the 4-intersection model) or 3 × 3 (in the 9-intersection model) matrix. In these matrices, each element, which may be either 0 or 1, denotes whether the corresponding intersection (e.g. $I(X) \cap I(Y)$) is empty (0), or not empty (e.g. possible) (1). Since the 4-IM only considers interiors and boundaries, it identifies eight possible base relations: *disjoint, meet, overlap, covers, covered by, equal, inside*, and *contains*. Compared with the 4-IM, the 9-IM provides more details for objects with co-dimension > 0 (Egenhofer et al., 1993). An advantage of the 9-IM is its capacity to model topological relations where point or line objects are involved (Egenhofer and Herring, 1991). Moreover, the 9-IM can also be adopted to represent the topological relations between two complex objects (Behr and Schneider, 2001). The intersection model (or region connection calculus proposed by Randell et al. (1992)) provides a sound categorization for infinitely topological relations, and two relations with identical 9-intersection matrices may still be topologically different (Egenhofer, 1993; Egenhofer and Franzosa, 1994; Liu and Shi, 2007). Both the 4-IM and 9-IM cannot perfectly deal with regions with holes, which can occur in OBIA (a lake with an island for example), and thus an additional component is necessary for this situation (Egenhofer et al., 1994; Chen et al., 2001). In this paper, we start with the 4-intersection model because of its simplicity and ability in distinguishing most base topological relations discussed in this research.

In addition to topological relations, binary spatial relations involving distance and direction are also important in classifying objects, and a number of algorithms exist to calculate distance (e.g. Euclidean distance between object centroids, or the major angle from centroid to centroid to determine the cardinal direction between two objects (Longley et al., 2005). These non-topological rules have also been employed to help enhance topological relations. For example, Mark (1999) argued that distance relations and direction relations can be regarded as refinements to disjoint topological relations. All three types of relations, topological, qualitative distance, and direction, are typically formalized using crisp logic, and indeed, in the commercial GIS software packages built on such a framework, a function that examines if two objects have a specific relation always returns a "crisp" value, i.e. "true" or "false". More recent work examining semi-quantitative representations (Bloch, 2003, 2005; Du et al., 2004; Dutta, 1991; Takemura et al., 2005), and fuzzy relations allows a more nuanced understanding of these relations.

These more comprehensive qualitative spatial relations have many uses, and come into play recently within a new paradigm for classification of high spatial resolution imagery: object based image analysis. However, in the OBIA context, each image segment has two important characteristics: (1) each segmented object consists of at least one pixel and thus is areal, with area and perimeter definition, and (2) any two segmented objects cannot overlap, and all objects thus form a single-valued space (detailed description about single-valued space will be discussed in the following section). In this context, the segmented images have unique characteristics and present an interesting case that has not been examined in the previous literature on spatial relations: we need to develop a framework for the spatial relations between non-overlapping spatial entities that are produced by image segmentation algorithms. Such a framework will aid in the second step of the OBIA process, segment classification.

1.2. Single-valued space

Spatial relations, specifically topological relations, are typically defined in multi-valued space. In other words, a point can belong to two different objects simultaneously if the objects overlap. In single-valued space, a point can only belong to one object: there can be no overlaps. A single-valued space is hereby defined as a specialized Euclidean space where there is only one value associated with a position inside the space. We argue that single-valued space is a commonly utilized spatial data format. For example, in land cover or habitat maps, objects cannot have two different properties under one classification system, and are thus embedded in a single-valued space. This is also the case with the results of most image segmentation algorithms.

In single-valued space, the formalization of topological spatial relations between two objects is simple. Following the 4-intersection model, spatial relations between two areal objects X and Y can be handled in

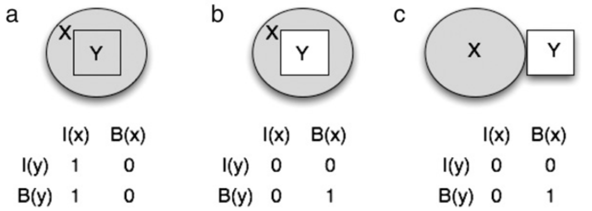


Fig. 2. Topological relations in multi-valued space versus single-valued space. (a) X contains Y in multi-valued space; (b) X contains Y in single-valued space; and (c) X meets Y in either single- or multi-valued space.

two cases: $B(X) \cap B(Y) = \emptyset$ and $B(Y) \cap B(X) = \neg\emptyset$, since $I(X) \cap I(Y)$, $I(X) \cap B(Y)$, and $B(X) \cap I(Y)$ are always empty due to the constraint of single-valued space. Thus the two possible spatial relations are *disjoint* and *meet* in the intersection model without considering holes. Unfortunately, only two relations are not enough in the context of spatial cognition. In other words, we usually perceive and express more than those two relations even in a single-valued space. Such relations may or may not be topologically equivalent. As we will see in Section 2.1, the latter cases, which are actually not topological relations, are defined based on normal topological relations or can be described using the same words. We thus name them "quasi-topological" relations.

A typical example that beyond the scope of those two relations is a proposition: "an island is inside a lake". There is an ontological consideration in this example, that is, whether an island is part of a lake. In single-valued space, the island is not viewed as part of the lake. However, it does not influence the reasonableness of such a proposition. As shown in Fig. 2, the 4-I matrix of case b is identical with that of case c. However, case b is often viewed as "X contains Y"; while case c is "X meets Y". The *contains* relation in multi-valued space is illustrated in Fig. 2(a). Its 4-I matrix is clearly different from that of case (b) and (c). Consequently, in single-valued space, we can identify a new relation (Fig. 2(b)) other than *disjoint* and *meet*. This relation can be expressed using the same word (i.e. contains) that is often used for a topologically different relation in multi-valued space, however, we use the term *surround* in this paper to avoid confusion. For example, the relation depicted in Fig. 2(b) can be expressed as "X surrounds Y" or "Y is surrounded by X". Note, case b and c are also not homeomorphous, and the 9-IM can distinguish them, since $E(X) \cap B(Y) = \emptyset$ in Fig. 2(b), while $E(X) \cap B(Y) = \neg\emptyset$ in Fig. 2(c). Unfortunately, the 9-IM also fails to distinguish case b and c when Y in case b has one or more hole.

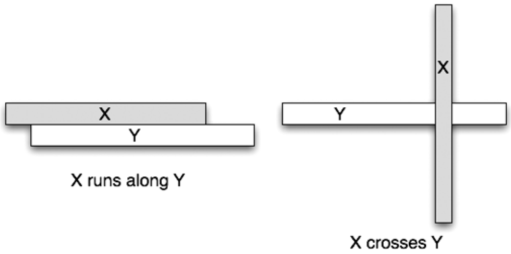


Fig. 3. Spatial relations between line-like objects (LLO) (In the second case, Y consists of two LLOs).

1.3. Adding object shape into the process

In real geographic space, most features have an areal extent; rarely is there an instance of a pure line or a point feature. Some features, such as rivers, roads, and cities for example, are rendered cartographically using line or point symbols on a small-scale map; nevertheless, they could be represented as regions if the map scale is sufficiently large. In a two-dimensional single-valued space S, a region O is defined to satisfy the following three conditions:

1. It is connected, i.e. for every pair of points in O, there is a line (not necessarily a straight one) joining these two points so that all the points on the line are also in it;
2. It is a topological closure, that is, $O = I(O) \cup B(O)$ and $E(O)$ is open. Moreover, for any two objects in S, the intersection of their interiors is empty. This feature makes that any two objects cannot overlap;
3. It may contain at least one hole.

Besides the above conditions, we can identify special areal features that are usually abstracted to points or lines in a specific scale according to their shapes and sizes. In this paper, we name these features "point-like objects" (PLO) and "line-like objects" (LLO). In addition to the relations that defined with viewing them as ordinary regions, spatial relations between PLOs or LLOs have specialized characteristics. For example, as shown in Fig. 3, let X and Y be two line-like objects. The following two propositions are reasonable: "X runs along Y" and "X crosses Y". Clearly, the spatial relations are described using terms that are used for topological relations between two lines. Nonetheless, the spatial relations depicted in Fig. 3 are not purely topological relations. Some non-topological properties, such as the objects' shapes and sizes, should also be considered to model such relations.

In addition to those three constraints for regions, point- and line-like objects are scale dependent. For an object to be considered as a line-like object, it should be long enough and narrow enough (Fig. 4(a)). We can constrain this decision with thresholds. Suppose there are two thresholds: width and length. A line-like object O under a length threshold $2l$ and a width threshold $2d$ is an areal object that satisfies:

$$\forall p \in O(\exists p' \in O, \mathit{Innermindist}(O, p, p') \geq l) \quad (1)$$

$$\forall p \in O(\exists p' \notin O, \mathit{Euclideandist}(p, p') \leq d), \quad (2)$$

where *Euclideandist* is a function to compute the Euclidean distance between two points; while *Innermindist* is a function to compute the minimal distance of a path between two points in O under the constraint that the path is inside O. To implement *Innermindist* is rather difficult in vector representation. However, it is relatively straightforward when calculating the patch in raster format, and there are a number of algorithms available, such as the cellular automata based approach (Tzionas et al., 1992). Obviously, the first condition (Eq. (1)) indicates that the object is long enough (for each point p inside O, we can find another point p' inside O such that *Innermindist* $(O, p, p') > l$); while second one specifies (Eq. (2)) that the object is narrow enough (for each point p inside O, we can find another point p' outside O such that *Euclideandist* $(p, p') < d$). We can thus name them "longness condition" and "narrowness condition" respectively. For a LLO, its length can be defined as:

$$l(O) = \max\{\mathit{Innermindist}(O, p, p') | p \in O, p' \in O\}. \quad (3)$$

In other words, for a LLO with length L, the two points that satisfy *Innermindist* $(O, p, p') = L$ should be both on the boundary of O. Since the width of an LLO is not constant, it can be represented using maximal width. For a point p inside O, another point p' outside O can be found to minimize the Euclidean distance between p and p'. Let the minimal distance be m. Taking into account all points inside O, we can obtain a set of m. The width of O can be given by doubling the maximal value in this set.

$$w(O) = 2\max\{\inf\{\mathit{Euclideandist}(p, p') | p' \notin O\} | p \in O\}. \quad (4)$$

Since the $E(O)$ is an open set, we employ infimum (defined as a greatest lower bound) instead of minimum to define $w(O)$. According to Eqs. (1)–(4), for an LLO satisfying threshold $2l$ and $2d$, the following two equations hold:

$$l(O) \geq 2l \quad (5)$$

$$w(O) \leq 2d. \quad (6)$$

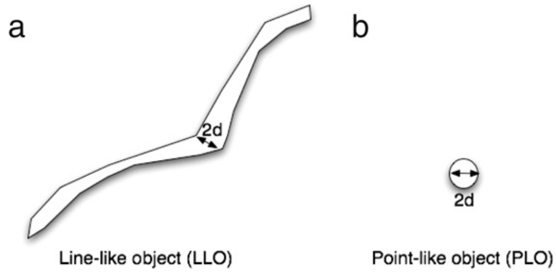


Fig. 4. (a) Line-like object, and (b) Point-like object.

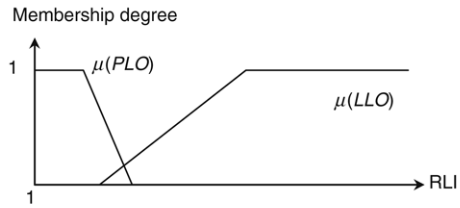


Fig. 5. Conceptual membership functions for areal objects based on relative longness index (RLI).

In contrast to LLOs, a PLO O (Fig. 4(b)) under width threshold $2d$ and length threshold $2l$ is an areal object that satisfies:

$$\forall p \in O(\forall p' \in O, \mathit{Innermindist}(O, p, p') \leq 2l) \quad (7)$$

$$\forall p \in O(\exists p' \notin O, \mathit{Euclideandist}(p, p') \leq d). \quad (8)$$

where the second condition is same with that of LLOs, while the first one indicates the object is not long (for every two points inside O, the shortest path connecting them is not greater than $2l$ with the constraint the path is also inside O). In practice, l and $d$are approximately equal for a PLO. In this paper, if an areal object cannot (or need not) be identified as LLO or PLO, we name it an ordinary areal object (OAO).

The above definitions for line- and point-like objects are crisp. However, the boundary between LLOs and PLOs is not always determinate, and a membership function can thus be defined for LLO and PLO classification that makes use of a shape index. In the membership function, we can employ $l(O)/w(O)$ to describe the relative long-ness index (RLI) for an areal object O. The range of RLI is greater than or equal to 1 according to the definitions of $l(O)$ and $w(O)$. It can be trivially proved that RLI $= 1$ for circular regions; while RLI > 1 regions in other shapes. If an object satisfies the narrowness condition, its RLI should be large enough to be a LLO; otherwise, the object may be a PLO. Hence, LLO and PLO can be viewed as two fuzzy sets, with a membership function based on RLI (Fig. 5).

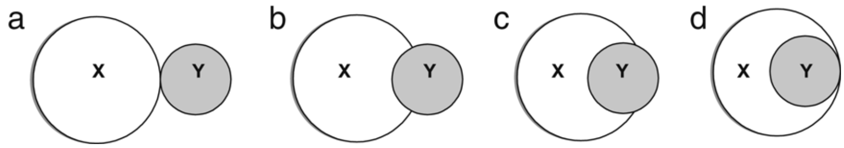


Fig. 6. Gradual changes of quasi-topological relations.

2. Region-based spatial relations in single-valued space

In this section, we will establish a framework of region-based spatial relations that covers quasi-topological relations, cardinal direction relations, and qualitative distance relations. As mentioned earlier, some relations are not purely topological although they can be described using similar terms, such as "cross". Additionally, since the boundaries between some spatial relations are not crisp, we define the predication based on fuzzy set theory.

2.1. Quasi-topological relations

A quasi-topological relation may not satisfy the normal constraint of topology — that relations remain unchanged despite transformation. Supposing there are two areal objects A and B, they may be LLOs or PLOs. Besides the conventional topological relation between them, their quasi-topological relation is influenced by their actual shapes.

2.1.1. Relations between two areal objects

According to the 4-intersection model, we can identify eight base topological relations between two regions (X and Y). However, in single-valued space, some relations are impossible since $I(X) \cap I(Y) = \emptyset$. In this research, for each conventional topological relation, we enforce that $I(X) \cap I(Y)$, and sometimes $I(X) \cap B(Y)$ or $B(X) \cap I(Y)$, belong to X or Y to see whether some relations can be found. Clearly, for *disjoint*, the situation does not change. For *contains* (or *inside*), it is the case that discussed in Section 1.2. In terms of *equal*, one object will disappear and thus the resulting relation is impossible. It is a bit complicated for other four relations. Suppose X *covers* Y, Y will disappear if $I(X) \cap I(Y)$and $I(X) \cap B(Y)$are merged to X. On the other hand, if $I(X) \cap I(Y)$belong to Y(Fig. 6(d)) (note that $B(X) \cap I(Y) = \emptyset$ when X *covers* Y), the relation that X is *invaded by* Y is suitable to describe this case (Aksoy et al., 2003). The inverse of *invadedBy* is *invade*, that is Y *invades* X as in Fig. 6(d). Moreover, we may declare X simply meets (*s-meet*) Y if there is not apparent invasion between X and Y. Finally, if X overlaps Y or X meet Y in multi-valued space, the corresponding relation after the mergence may be *invade*, *invadedBy*, or *s-meet*, depending on actual shapes of X and Y. It should be noted that *invade*, *invadedBy*, and *s-meet* are topologically equivalent. Fig. 6 depicts gradual changes of the regular topological relation *meet*. Following fuzzy set theory, we introduce a number varying from 0 to 1 to describe the degree that each situation belongs to a relation. Intuitively, the degree that the relation depicted in Fig. 6(a) belongs to *s-meet* will be close or equal to 1, while this relation belongs to *invade* and *invadedBy* will be close or equal to 0. A similar gradual change framework in multi-valued space is discussed in Egenhofer and Al-Taha (1992), where relations are represented by different 9-I matrices.

Consequently, with the constraint of single-valued space, we can discriminate six quasi-topological relations: *disjoint*, *surroundedBy*, *surround*, *invade*, *invadedBy*, and *s-meet* (Table 1). These six relations can be classified into two categories based on their 4-I matrices. The first group, with 4-I matrix

$$\begin{array}{lcc} & I(X) & B(X) \\ I(Y) & 0 & 0 \\ B(Y) & 0 & 0 \end{array} \tag{9}$$

includes *disjoint*. The second one consists of the remaining five relations. The corresponding 4-I matrix is:

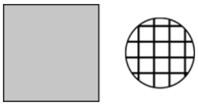
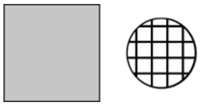
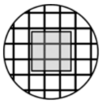
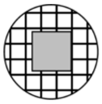
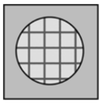
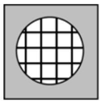
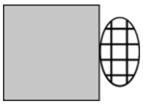
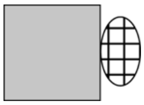
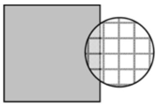
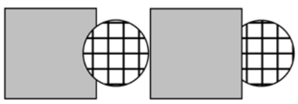
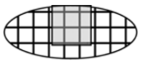
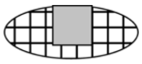
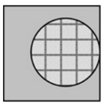
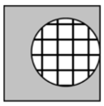
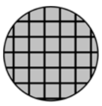
$$\begin{array}{lcc} & I(X) & B(X) \\ I(Y) & 0 & 0 \\ B(Y) & 0 & 1. \end{array} \tag{10}$$

Moreover, the second category can be grouped into three topologically different subsets. They are {*s-meet, invade, invadedBy*}, {*surroundedBy*}, and {*surround*}. Since *s-meet, invade*, and *invadedBy* are topologically equivalent, they should be defined quantitatively such that we can distinguish them.

1. Disjoint

   As mentioned earlier, the 4-I matrices of disjoint relation and others are different at the element of $B(X) \cap B(Y)$, hence the *disjoint* relation between two

Table 1
Quasi-topological relations between two OAOs in single-valued space

Topological relation	Multi-valued space	Single-valued space	Quasi-topological relation
"disjoint"			"disjoint"
"inside"			"surroundedBy"
"contains"			"surround"
"meet"			"s-meet", "invade", or "invadedBy" (the degree of s-meet is usually high)
"overlap"			"s-meet", "invade", or "invadedBy"
"coveredBy"			"s-meet", "invade", or "invadedBy" (the degree of "invades" is usually high)
"covers"			"s-meet", "invade", or "invadedBy" (the degree of "invadedBy" is usually high)
"equal"		N/A	

areal objects in single-valued space can be defined as:

$$disjoint(X, Y) = \begin{cases} 1, & \text{if } B(X) \cap B(Y) = \emptyset \\ 0, & \text{if } B(X) \cap B(Y) \neq \emptyset. \end{cases} \quad (11)$$

In this study, since an object may contain one or more hole, three sub-cases can be identified for the *disjoint* relation. These three sub-cases are topological different, and cannot be distinguished even by the 9-intersection model (Fig. 7). The V9-IM (Chen et al., 2001), which is an extension of the 9-intersection model that considers Voronoi diagrams, provides a suitable solution for them.

2. Surround and surroundedBy

Although the 4-I matrices of *surroundedBy* and *surround* are identical to that of *invadedBy*, *invade*, and *s-meet*, they are not homeomorphous. If X is surrounded by Y, the intersection of $B(X)$ and $B(Y)$ should be a closed line that is homeomorphous to a circle, and the convex hull of X should be a subset of the convex hull of Y. Let $H(O)$ denote the convex hull of an object O. The s*urroundedBy* relation can therefore be defined as:

$$surroundedBy(X, Y) = \begin{cases} 0, & \text{if } B(X) \cap B(Y) = \emptyset \\ 1, & \text{if closed}(B(X) \cap B(Y)) \wedge H(X) \subset H(Y), \end{cases} \quad (12)$$

where *closed* is a function to check if a line is closed. Note that we employ such a definition instead of a simple predication $B(X) \subset B(Y)$, since X may contain holes. *Surround* and s*urroundedBy* are two inverse relations. We thus have:

$$surround(X, Y) = surroundedBy(Y, X) \quad (13)$$

3. S-meet, invade, and invadedBy

As mentioned earlier, these three relations should be quantitatively defined. Intuitively, if X invades Y,

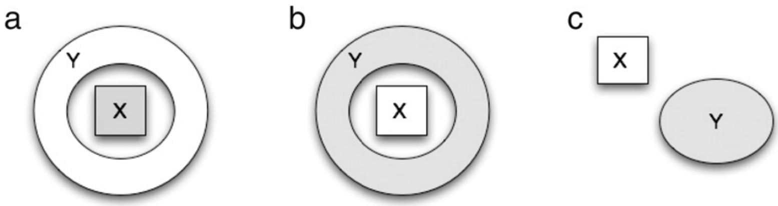


Fig. 7. Three sub-cases of "disjoint" relations.

then $H(X) \cap H(Y)$ is close to $H(X)$. On the contrary, if $H(X) \cap H(Y)$ is close to 0, then the relation between X and Y tends to be what we call "*s-meet*" or a simple meeting. Following this point, *s-meet* relation is defined as:

$$s\text{-}meet(X, Y) = \begin{cases} 0, & \text{if } B(X) \cap B(Y) = \emptyset \\ 1 - \dfrac{area(H(X) \cap H(Y))}{\min(area(H(X)), area(H(Y)))}, & \\ \text{if } B(X) \cap B(Y) \neq \emptyset \end{cases} \quad (14)$$

where *area* is a function to compute the area of a region. If X completely invades Y, we can infer that $H(X) \subset H(Y)$. This results in the formulations:

$$\frac{area(H(X) \cap H(Y))}{\min(area(H(X)), area(H(Y)))} = 1 \quad (15)$$

and

$$s\text{-}meet(X, Y) = 0. \quad (16)$$

The case that X invades Y is topologically equivalent to the case that X simply meets Y. If the relation between X and Y is *disjoint*, *surround*, or *surroundedBy*, then $invades(X, Y) = 0$, otherwise, it is defined as:

$$invades(X, Y) = \frac{area(H(X) \cap H(Y) \cap X)}{area(X)} \quad (17)$$

Contrarily, the relation X is invaded by Y can be defined as:

$$invadedBy(X, Y) = invades(Y, X). \quad (18)$$

It should be noted that there are other quantitative approaches to measure the degrees of *s-meet, invade*, and *invadedBy*. For instance, Aksoy et al. (2003) proposed perimeter-based definitions to represent them. However, if X and/or Y have holes, the perimeter-based definitions are not reasonable.

Up to this point, we have defined six region/region quasi-topological relations. Among them, *disjoint*, *surround*, and *suroundedBy* are crisp relations, while *s-meet*, *invade*, and *invadedby* are relations with fuzziness and quantitatively defined. For example, for a gradual relation, say *invade*, if $invade(X, Y)$ is greater than a threshold, say 0.8, we can express that X invade Y. Table 2 demonstrates some cases and lists the values for these six relations. The selection of threshold is beyond the scope of this research. We plan to investigate this in the future.

2.1.2. Relations between two line-like objects

Topological relations between two lines are inherently more complicated than those between two areas. In Egenhofer and Herring (1991), 33 relations between two simple lines and 24 relations between non-simple lines are presented. However, only a few line-line relations are identified in natural language. For instance, Xu (2007) identified 10 relations, which may be not topological, such as "is parallel to", to be investigated based on cognitive experiments. For two line-like objects (LLOs), in addition to the six quasi-topological relations (Section 2.1.1) by viewing them as ordinary areal objects (OAOs), more relations may be identified with assuming they are abstracted to two-dimensional real lines. In Table 3, we illustrate five relations between two lines as well as between two LLOs when they are both connected. These relations, including *along*, *connect*, *merge*, *mergedWith*, and *l-meet*, are homeomorphous and shape dependent. In addition to these five relations, *crosses* is a tertiary relation where three LLOs are involved in due to the constraints of single-valued space. If the relation between two LLOs is *disjoint*, some special relations (e.g. parallel) can be identified. The method proposed by Xu (2007) can be employed to deal with such relations.

1. Along

   The *along* relation between two LLOs is dependent on the length of the intersection of their boundaries. It is thus defined as:

$$along(X, Y) = \frac{length(B(X) \cap B(Y))}{length(B(X))}, \quad (19)$$

   where *length* is a function to compute the length of a typical linear object. Two issues of the *along* relation should be noted. First, it is not symmetrical. As shown in Fig. 8(a), $along(Y, X) > along(X, Y)$.

Table 2
Quantitative representation of quasi-topological relations

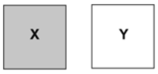
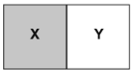
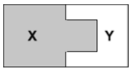
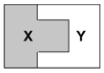
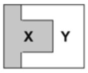
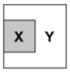
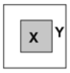
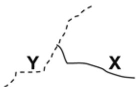
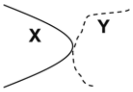
	"disjoint"	"surround"	"surroundedBy"	"s-meet"	"invade"	"invadedBy"
	1	0	0	0	0	0
	0	0	0	1	0	0
	0	0	0	0.625	0.2	0.167
	0	0	0	0.571	0.333	0.167
	0	0	0	0.4	0.5	0.167
	0	0	0	0	1	0
	0	0	1	0	0	0

Table 3
Quasi-topological relations between two line-like objects in single-valued space

Relation	Multi-valued space & line object	Single-valued space & line-like object
"along"		
"connect"		
"merge"		
"mergedWith"		
"l-meet"		
"crosses"		

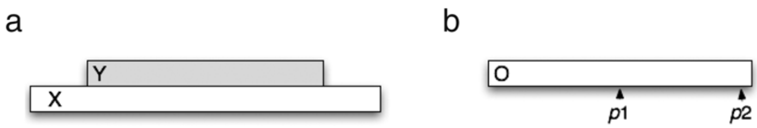


Fig. 8. Relations between two line-like objects (LLO): (a) "along" relation between X and Y; (b) header of a LLO. p1 is the center point of the line and p2 is the end point.

Second, since $B(X)$ and $B(Y)$ include two sides, whose lengths are roughly equal, *along*(X, Y) usually varies from 0 to 0.5.

2. Connect, merge, mergedWith, and *l*-meet

Different from *along*, the length of the intersection of two objects' boundaries should be short for these four relations, in other words, $length(B(X) \cap B(Y))$ should be smaller than a threshold, which can usually be set to $w(X)$ or $w(Y)$. Additionally, in order to discriminate *connect*, *merge*, *mergedWith*, and *l-meet*, we should consider how X and Y are adjacent. If a "header point" can be found in the boundary of each LLOs, then we can express that X connects Y when both the header of X and the header of Y are within $B(X) \cap B(Y)$, X merges Y or Y is merged with X only when the header of Y is within $B(X) \cap B(Y)$, and the relation is *l-meet* when neither the header of X nor the header of Y is within $B(X) \cap B(Y)$. A line-like object O usually has two headers. Each of them can be defined as a point p that satisfies the following condition: another point p' can be found within $B(O)$ such that $Innermindist(O, p, p') = l(O)$. Actually, such a definition is a bit strict, since another point close to p can still be viewed as the header of O. A metric, *headerness*, is thus introduced to measure the degree that a point p within $I(O)$ or $B(O)$ belong to the header of a LLO O. It is defined as:

$$headerness(p, O) = \frac{2 \max\{Innermindist(O, p, p') | p' \in O\}}{l(O)} - 1 \quad (20)$$

According to Eqs. (1), (3) and (5), this metric varies from 0 to 1. As shown Fig. 8(b), $headerness(p_1, O)$ is close to 0, while $headerness(p_2, O)$ is close to 1. Based on Eq. (20), for a subset of O, we can compute its headerness by summarising all point within it using different statistics, such as minimum, maximum, and average. For instance, if maximum is selected, the definition is:

$$headerness(O', O) = \max\{headerness(p, O) | p \in O'\}, \quad (21)$$

where O' denotes a subset of O. Following the above discussion, *connect*, *merge*, *mergedWith*, and *l-meet* can be defined base on Eq. (21).

$$connect(X, Y) = headerness \times (X \cap Y, X) headerness(X \cap Y, Y) \quad (22)$$

$$merge(X, Y) = (1 - headerness \times (X \cap Y, X)) headerness(X \cap Y, Y) \quad (23)$$

$$mergedWith(X, Y) = headerness(X \cap Y, X) \times (1 - headerness(X \cap Y, Y)) \quad (24)$$

$$l - meet(X, Y) = (1 - headerness(X \cap Y, X)) \times (1 - headerness(X \cap Y, Y)). \quad (25)$$

3. Crosses

In single-valued space, *crosses* is a ternary relation. When we express that X crosses Y, Y is broken into two parts by X. Let these two parts be Y_1 and Y_2. $CR(X, Y_1, Y_2) = 1$ if the following two conditions hold:

$$merge(X, Y_1) \geq t_1 \wedge merge(X, Y_2) \geq t_2 \\ \exists p_1 \in Y_1, p_2 \in Y_2 (Euclideandist(p_1, p_2) \leq t_3), \quad (26)$$

where t_1, t_2, and t_3 are three thresholds. In practice, we can set t_1 and t_2 close to 1, and set t_3 according to the width of X, that is $w(X)$. Eq. (26) implies that X crosses Y_1 and Y_2 implies that they are close enough and simultaneously merged with X.

2.1.3. Relations between two point-like objects

The relations between two ordinary points as well as two PLOs are relatively simple, and include *equal* and *disjoint*. For two LLOs, their sizes are small such that their actual shapes can be neglected. Hence, we only identify two relations between two LLOs: *disjoint* and *s-meet*, which are defined as being the same as those between two OAOs.

Besides the above three categories of quasi-topological relations, the relations between OAO versus LLO, OAO versus PLO, and LLO versus PLO can be similarly defined. Nevertheless, the actual shapes of the involved object should be considered in corresponding definitions.

2.2. Direction relations

Direction relations and metric relations between two objects are usually considered when they are not overlapping. These two categories of relations thus do not require substantial revision for single-valued space. However, for the completeness of the proposed framework, we provide a brief discussion about them. In OBIA, an image is required to be oriented in order to apply cardinal direction relation. Some cardinal direction relation models, such as the cone-based model, the project-based model (Frank, 1991), and the minimal bounding rectangle (MBR)-based model (Goyal and Egenhofer, 2000), have been presented for objects in two-dimensional space. Generally, the cone-based model and the project-based model are suitable when the reference object is a

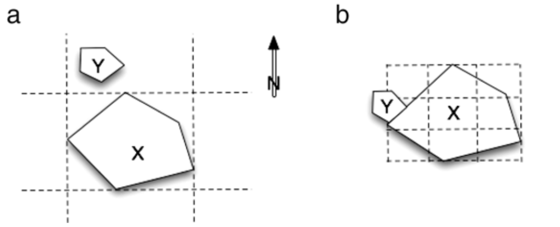


Fig. 9. Cardinal direction relations in single-valued space for (a) two disconnected regions (Y is north of X), and (b) two adjacent regions (Y is west of X).

point, while the minimum boundary-based model is more appropriate for linear or areal reference objects. In the framework proposed in this paper, since all objects are areal, the MBR-based model can be directly adopted (Fig. 9(a)). However, if the reference object is a point-like object, both the cone-based model and the project-based model are also acceptable. Besides these crisp models, Bloch (2005) summarized some fuzzy approaches to represent direction relations, such as a compatibility method based on histogram of angles, aggregation method, histogram of forces, projection based approach, and morphological approach. Another available model considering fuzziness is proposed in Claramunt and Thériault (2004). It should be noted that cardinal direction relations also make sense when two areal objects are connected. For example, “Portugal is west of Spain” is a true statement. In addition to above models, an alternative approach is extending the internal cardinal direction (ICD) model presented in Liu et al. (2005). With an ICD model, the boundary of a reference object X can be divided into a number of linear parts, then for the object Y, its relation to X depends on to which of these parts Y is connected. For example, if Y is connected to the western part of X, then Y is considered to be west of X (Fig. 9(b)).

2.3. Qualitative distance relations

The qualitative distance relation between two objects makes sense only when the topological relation between them is *disjoint*. It is well-known that the qualitative distance relation between two objects relies on their sizes in addition to the quantitative distance between them. As shown in Fig. 10, the absolute distances between two objects in (a) and (b) are equal, however, the qualitative distance in (a) is often believed to be smaller than that in (b) due to sizes of involved objects.

Taking the objects' size into account, the relative distance between two areal objects can be defined as:

$$RelDistance(X, Y) = \frac{AbsDistance(X, Y)}{\sqrt[4]{area(H(X))area(H(Y))}}, \quad (27)$$

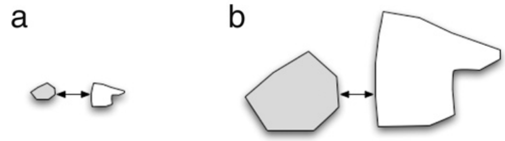


Fig. 10. Qualitative distances between two groups of objects with different sizes: (a) small objects and (b) large objects.

where $AbsDistance(X, Y)$ is used to compute the absolute distance between X and Y. In practice, it could be calculated either based on the centroids of X and Y or the nearest distance between X and Y. Then the qualitative distance between two objects can be obtained by classifying the relative distance into a group of distinctions, such as *far* and *close*, with or without considering the fuzziness of each distinction. Note that qualitative distances based on Eq. (27) is symmetric, that is, the distance from X to Y equals to the distance from Y to X. However, some researchers argue that qualitative distances are asymmetric (Egenhofer and Mark, 1995; Clementini et al., 1997). We can thus adjust the objects' weight according to their sizes, which can be represented by $area(H(X))$ and $area(H(Y))$, in Eq. (27).

3. Applications in high resolution remotely sensed imagery classification

It has been mentioned earlier that the proposed definitions for point- and line-like objects and their associated relations can be used to build rules for classifying high spatial resolution remotely sensed imagery. This is demonstrated here using traffic flow analysis from high resolution remotely sensed imagery, showing that our method provides a convenient approach for road extraction and vehicle detection (Agouris et al., 2002; Niu, 2006). In this case study, we will employ the proposed spatial relations to identify roads and moving vehicles on them. The study area is near Berkeley, California. Fig. 11(a) depicts the original aerial photo with spatial resolution of 0.3 meter. It contains two roads: Highway 80 on the west side and Pierce Street on the east side of the image. The spatial resolution of the image is high enough to enable direct counting of the vehicles moving on the roads (Table 4).

The image was first segmented into a set of areal objects using Definiens®5.0 (Baatz and Schape, 2000). We tested different parameter settings to find an appropriate one that can separate most vehicles from roads. In order to extract roads and moving vehicles from the segmented image, the following two rules are adopted:

Table 4
The number of moving vehicles identified from the high spatial-resolution remotely sensed imagery of the study area

	Highway 80	Pierce street
Ground truth by visual interpretation	23	15
Segmented correctly by Definiens®	19[a]	2
Identified after using the two initial rules	11	1
Identified after using the third rule	24	1
Left after using the fourth rule	21	1

[a] A truck is segmented into 3 objects, and a car is segmented into 2 objects.

Fig. 11. (a) The original image and (b) the segmented result, where the grey scale of each object represents its relative longness index (RLI), and the extracted moving vehicles are shown in red.

(1) *A road is a line-like object, or consists of a number of lanes that are LLOs.*

(2) *The moving vehicles are non-line-like objects surrounded by or invading a road or a lane. In addition, their areas should be between two limits, i.e. a vehicle cannot be too large or too small in the RS image.*

A computer program was developed to calculate the relative longness index (RLI) of the resulting objects. In the program, the function *Innermindist* is implemented using the algorithm mentioned in Longley et al. (2005). The RLIs of the objects are represented using different grey scales (Fig. 10(b)). From Fig. 10(b), we may identify Highway 80 clearly. It consists of a set of lanes with high RLI values. Employing the trial and error method, the threshold of RLI is set to be 12 such that Highway 80 and part of Pierce Street can be extracted. As shown in Table 4, most of the vehicles in Pierce Street are not segmented correctly. Definiens uses a multi-scale region-based segmentation method; several thresholds are important to segment an image such as color, shape, smoothness and compactness. Because of the significant difference of spectral reflectance between Highway 80 and Pierce Street (Fig. 11(a)), it is difficult for the algorithm to find the universal thresholds to segment both roads well, which may contribute to the incorrect segmentation of Pierce Street. Because of that, we focused here on extracting the vehicles on Highway 80. The moving vehicles can be discerned (Table 4, the 3th row) based on corresponding spatial relations (should be *surroundedBy* and *invade*) and the area constraint. In this case study, the areas of potential vehicle objects vary from 60 pixels to 360 pixels, i.e. about from 5.4 m^2 to 32.4 m^2. Due to the mixed pixels at the edge and the segmentation algorithms, this range is often a bit wider than that of the actual car sizes. With the precondition that vehicles can be clearly identified, lower resolution will make the range wider, and vice versa. For instance, in Jin and Davis (2004), the size range based on 1m IKONOS imagery is 3 m^2 to 40 m^2. However, there are some cases that two lane objects are not connected due to a vehicle between them. Consequently, the *surroundedBy* and *invade* relations cannot be employed to extract the vehicles. We thus add a third rule for them:

(3) *The moving vehicles may also be areal objects neighbouring to a road or a lane.*

After this rule was adopted, a total of 23 "moving vehicles" on Highway 80 are identified. This result concurs with the ground truth. However, it is not correct since only 19 vehicles were segmented by Definiens®. Some vehicles were wrongly segmented into more than one object. It led to the additional falsely identified vehicles. We thus introduce the fourth rule to deal with these cases:

(4) *If the spatial relation between two objects being classified as "vehicles" is close, then they should be merged.*

Rule 4 reduces the results to 3 objects (Table 4, the 5th row). In this case study, according to the definition of qualitative distance relations, the relation "close" is defined as: if the distance between the centres of two areal objects, say X and Y, is smaller than or equal to two times of their average size, that is, $RelDistance(X, Y) < 2$ (please see Eq. (27)), then these two objects are close. Note that the *close* relation in this case study is crisply defined without considering its fuzziness.

A computer program based on Microsoft Visual C++ was implemented to examine the spatial relations and extract the moving vehicles automatically (Fig. 11(b)). It identified all 19 vehicles with only two misclassified (one on Highway 80). The result indicates the reasonableness of the above four rules, as well as the proposed framework of spatial relations. Note in this case study, a truck (marked to be yellow in Fig. 11(b)) in Pierce Street is not correctly recognized, since the areal objects surrounding it is recognized to be a road due to low RLI. In order to deal with this situation, new rules that consider spectral attributes in addition to shape attributes should be introduced to classify roads. Meanwhile, the segmentation methods are important for the classification results. As we mentioned above, the Definiens®5.0 did not perform well in segmenting the vehicles on Pierce Street. There are a large variety of segmentation methods that have been developed; it is commonly believed that no universal segmentation method that can be used for all types of land cover types (Pal and Pal, 1993; Zhang and Luo, 2000; Carleer et al., 2005). Although discussion on segmentation methods are beyond the scope of this research, it should be noted that the final classification accuracy not only depends on the classification rules that are derived from the proposed spatial relations framework, but also depends on the initial segmentation results.

4. Conclusions

Image classification methods that utilize object based techniques are increasingly used in classifying high spatial resolution remotely sensed images. Because the spatial relations between objects play a critical role in identifying objects, in this paper, we proposed a framework of spatial relations that are suitable for segmented images (i.e. single-value space) that consist of the following three features: (1) the objects involved are actually regions such that line-like and point-like objects can be further distinguished; (2) the space is single-valued and any two objects inside it cannot overlap; and (3) the relations are semi-quantitative. In this framework, we reconsidered the three conventional spatial relations, i.e. topological relations, cardinal direction relations, and qualitative distance relations. This paper presents a case study demonstrating the extraction of roads and moving vehicles from a high spatial resolution image. This kind of application is increasingly common. While many of the most popular OBIA software packages in use today provide little information on classification algorithms, and hence can be quite "black-box", our rules are clearly defined and transparent. The result indicates that the framework provides a promising approach for building rules in the object-based classification process.

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References

Agouris, P., Doucette, P., Stefanidis, A., 2002. Automatic road extraction from high-resolution multispectral imagery. Technical Report. Digital Image Processing and Analysis Laboratory. Department of Spatial Information Science and Engineering, University of Maine, Orono, Maine.

Aksoy, S., Tusk, C., Koperski, K., Marchisio, G., 2003. Scene modeling and image mining with a visual grammar. In: Chen, C.H. (Ed.), Frontiers of Remote Sensing Information Processing. World Scientific, Singapore, pp. 35–62.

Baatz, M., Schape, A., 2000. Multiresolution segmentation: An optimization approach for high quality multiscale image segmentation. In: Strobl, J., Blaschke, T. (Eds.), Angewandte Geographische Informationsverabeitung. Herbert Wichmann Verlag, Heidelberg, Germany, pp. 12–23.

Behr, T., Schneider, M., 2001. Topological relationships of complex points and complex regions. ER. In: Lecture Notes in Computer Science, vol. 2224. Springer-Verlag, Berlin, pp. 56–69.

Benz, U.C., Hofmann, P., Willhauck, G., Lingenfelder, I., Heynen, M., 2004. Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. ISPRS Journal of Photogrammetry & Remote Sensing 58 (3–4), 239–258.

Blaschke, T., Hay, G., 2001. Object-oriented image analysis and scale-space: Theory and methods for modeling and evaluating multi-scale landscape structure. International Archives of Photogrammetry and Remote Sensing 34 (4/W5), 22–29.

Bloch, I., 2003. Fuzzy spatial relationships from mathematical morphology for model-based pattern recognition and spatial reasoning. In: Nyström, I., di Baja, G.S., Svensson, S. (Eds.), DGCI 2003. In: Lecture Notes in Computer Science, vol. 2886. Springer-Verlag, Berlin, pp. 16–33.

Bloch, I., 2005. Fuzzy spatial relationships for image processing and interpretation: A review. Image and Vision Computing 23 (2), 89–110.

Chen, J., Li, C.M., Li, Z.L., Gold, C., 2001. A Voronoi-based 9-intersection model for spatial relations. International Journal of Geographical Information Science 15 (3), 201–220.

Cheng, H.D., Jiang, X.H., Sun, Y., Wang, J., 2001. Color image segmentation: Advances and prospects. Pattern Recognition 34 (12), 2259–2281.

Carleer, A.P., Debeir, O., Wolff, E., 2005. Assessment of very high spatial resolution satellite image segmentations. Photogrammetric Engineering & Remote Sensing 71 (11), 1285–1294.

Claramunt, C., Thériault, M., 2004. Fuzzy semantics for direction relations between composite regions. Information Sciences 160 (1–4), 73–90.

Clementini, E., Di Felice, P., Hernández, D., 1997. Qualitative representation of positional information. Artificial Intelligence 95 (2), 317–356.

Du, S., Wang, Q., Yang, Y., 2004. Fuzzy description of fuzzy direction relations and their similarities. In: Proc. 12th International Conference on Geoinformatics — Geospatial Information Research: Bridging the Pacific and Atlantic, Gävle, Sweden, 7–9 Jun. 2004, pp. 496–502.

Dutta, S., 1991. Approximate spatial reasoning: Integrating qualitative and quantitative constraints. International Journal of Approximate Reasoning 5 (3), 307–330.

Egenhofer, M.J., 1991. Reasoning about binary topological relations. In: Günther, O., Schek, H.J. (Eds.), SSD-91. In: Lecture Notes in Computer Science, vol. 525. Springer-Verlag, Berlin, pp. 143–160.

Egenhofer, M.J., 1993. A model for detailed binary topological relationships. Geomatica 47 (3–4), 261–273.

Egenhofer, M.J., Al-Taha, K.K., 1992. Reasoning about gradual changes of topological relationships. In: Frank, A.U., Campari, I., Formentini, U. (Eds.), Theory and Methods of Spatio-Temporal Reasoning in Geographic Space. In: Lecture Notes in Computer Science, vol. 639. Springer-Verlag, Berlin, pp. 196–219.

Egenhofer, M.J., Clementini, E., di Felice, P., 1994. Topological relations between regions with holes. International Journal of Geographical Information Systems 8 (2), 129–142.

Egenhofer, M.J., Franzosa, R., 1991. Point-set topological spatial relations. International Journal of Geographical Information Systems 5 (2), 161–174.

Egenhofer, M.J., Mark, D.M., 1995. Naïve geography. In: Frank, A.U., Kuhn (Eds.), COSIT'95. In: Lecture Notes in Computer Science, vol. 988. Springer-Verlag, Berlin, pp. 1–15.

Egenhofer, M.J., Franzosa, R., 1994. On the equivalence of topological relations. International Journal of Geographical Information Systems 9 (2), 133–152.

Egenhofer, M.J., Herring, J., 1991. Categorizing binary topological relations between regions, lines and points in geographic databases. Technical Report, Department of Surveying Engineering, University of Maine, Orono, ME.

Egenhofer, M.J., Sharma, J., 1993. Topological relations between regions in R^2 and Z^2. In: Abel, D.J., Ooi, C.B. (Eds.), SSD-93. In: Lecture Notes in Computer Science, vol. 692. Springer-Verlag, Berlin, pp. 316–336.

Egenhofer, M.J., Sharma, J., Mark, D.M., 1993. A critical comparison of the 4-intersection and 9-intersection models for spatial relations: formal analysis. In: McMaster, R., Armstrong, M. (Eds.), Auto-Carto 11, Minneapolis, MN, pp. 1–11.

Frank, A.U., 1991. Qualitative spatial reasoning about cardinal directions. In: Proc. 7th Austrian Conference on Artificial Intelligence, Wien, Austrian, 24–27 Sep. 1991, pp. 157–167.

Goyal, R.K., Egenhofer, M.J., 2000. Consistent queries over cardinal directions across different levels of detail. In: Proc. IEEE 11th International Workshop on Database and Expert Systems Applications, Greenwich, UK, 6–8 Sep. 2000, pp. 876–880.

Guo, Q., Kelly, M., Gong, P., Liu, D., 2007. An object-based classification approach in mapping tree mortality using high spatial resolution imagery. GIScience & Remote Sensing 44 (1), 1–24.

Hay, G., Blaschke, T., Marceau, D., Bouchard, A., 2003. A comparison of three image-object methods for the multiscale analysis of landscape structure. ISPRS Journal of Photogrammetry & Remote Sensing 57 (5), 1–19.

Herold, M., Liu, X., Clarke, K., 2003. Spatial metrics and image texture for mapping urban land use. Photogrammetric Engineering & Remote Sensing 69 (9), 991–1002.

Jin, X., Davis, C.H., 2004. Vector-guided vehicle detection from high-resolution satellite imagery. In: Proc. IEEE Geoscience and Remote Sensing Symposium 2004, Anchorage, AK, 20–24 Sept. 2004, pp. 1095–1098.

Li, W., Benie, G.B., He, D.-C., Wang, S., Ziou, D., Gwyn, Q.H.J., 1999. Watershed-based hierarchical SAR image segmentation. International Journal of Remote Sensing 20 (17), 3377–3390.

Liu, K., Shi, W., 2007. Extended model of topological relations between spatial objects in geographic information systems. International Journal of Applied Earth Observation and Geoinformation 9 (3), 264–275.

Liu, Y., Wang, X., Jin, X., Wu, L., 2005. On internal cardinal direction relations. In: Cohn, A.G., Mark, D.M. (Eds.), COSIT 2005. In: Lecture Notes in Computer Science, vol. 3693. Springer-Verlag, Berlin, pp. 283–299.

Lobo, A., 1997. Image segmentation and discriminant analysis for the identification of land cover units in ecology. IEEE Transactions on Geoscience and Remote Sensing 35 (5), 1–11.

Longley, P.A., Goodchild, M.F., Maguire, D.J., Rhind, D.W., 2005. Geographic Information Systems and Science, second Ed. John Wiley & Sons Inc., New York.

Mark, D.M., 1999. Spatial Representation: A Cognitive View. In: Maguire, D.J., Goodchild, M.F., Rhind, D.W., Longley, P. (Eds.), Geographical Information Systems: Principles and Applications, Second Ed., vol. 1. John Wiley & Sons, New York, pp. 81–89.

McDonnell, R., Kemp, K., 1995. International GIS Dictionary. Geoinformation International, Cambridge.

Niu, X., 2006. A semi-automatic framework for highway extraction and vehicle detection based on a geometric deformable model. ISPRS Journal of Photogrammetry & Remote Sensing 61 (3–4), 170–186.

Pal, N.R., Pal, S.K., 1993. A review on image segmentation techniques. Pattern Recognition 26 (9), 1277–1294.

Randell, D.A., Cui, Z., Cohn, A.G., 1992. A spatial logic based on regions and connection. In: Proc. Third International Conference on Principles of Knowledge Representation and Reasoning (KR'92), Cambridge, MA, 25–29 Oct. 1992, pp. 165–176.

Renz, J., 2002. Qualitative Spatial Reasoning with Topological Information. In: Lecture Notes in Artificial Intelligence, vol. 2293. Springer-Verlag, Berlin.

Takemura, C.M., Cesar Jr., C., Bloch, I., 2005. Fuzzy modeling and evaluation of the spatial relation along. In: Lazo, M., Sanfeliu, A. (Eds.), CIARP 2005. In: Lecture Notes in Computer Science, vol. 3773. Springer-Verlag, Berlin, pp. 837–848.

Toll, D.L., 1984. An evaluation of simulated Thematic Mapper data and Landsat MSS data for discriminating suburban and regional land-use and land cover. Photogrammetric Engineering and Remote Sensing 50 (12), 1713–1724.

Tzionas, P., Tsalides, P., Thanailakis, A., 1992. Cellular automata based minimum cost path estimation on binary maps. IEEE Electronics Letters 28 (17), 1653–1654.

Wang, Z., Song, C., Wu, Z., Chen, X., 2005. Improved watershed segmentation algorithm for high resolution remote sensing images using texture. In: Proc. IEEE International Geoscience and Remote Sensing Symposium, Soul, Korea, vol. 5, 25–29 Jul. 2005, pp. 3721–3723.

Winter, S., Bittner, T., 2002. Hierarchical topological reasoning with vague regions. In: Shi, W., Fisher, P., Goodchild, M.F. (Eds.), Spatial Data Quality. Taylor & Francis, London, pp. 35–49.

Winter, S., Frank, A.U., 2000. Topology in raster and vector representation. GeoInformatica 4 (1), 35–65.

Xia, L., 1996. A method to improve classification with shape information. International Journal of Remote Sensing 17 (8), 1473–1481.

Xu, J., 2007. Formalizing natural-language spatial relations between linear objects. International Journal of Geographical Information Science 21 (4), 377–395.

Yao, X., Thill, J.C., 2006. Spatial queries with qualitative locations in spatial information systems. Computers, Environment and Urban Systems 30 (4), 485–502.

Zhang, Y.J., Luo, H.T., 2000. Optimal selection of segmentation algorithms based on performance evaluation. Optical Engineering 39 (6), 1450–1456.