Reasoning about spatial data is a key task in many applications, including geographic information systems, meteorological and fluid-flow analysis, computer-aided design, and protein structure databases. Such applications often require the identification and manipulation of qualitative spatial representations, for example, to detect whether one object will soon occlude another in a digital image or efficiently determine relationships between a proposed road and wetland regions in a geographic data set. Qualitative spatial reasoning (QSR) provides representational primitives (a spatial “vocabulary”) and inference mechanisms for these tasks. This article first reviews representative work on QSR for data-poor scenarios, where the goal is to design representations that can answer qualitative queries without much numeric information. It then turns to the data-rich case, where the goal is to derive and manipulate qualitative spatial representations that efficiently and correctly abstract important spatial aspects of the underlying data for use in subsequent tasks. This article focuses on how a particular QSR system, SPATIAL AGGREGATION, can help answer spatial queries for scientific and engineering data sets. A case study application of weather analysis illustrates the effective representation and reasoning supported by both data-poor and data-rich forms of QSR.

The ability to perceive spatial objects and reason about their relations seems effortless for humans but has proved so difficult for computers that they have yet to attain the capabilities of a five-year-old child. Part of the computational problem lies in the difficulty of identifying and manipulating qualitative spatial representations. For example, although the pixels in a digital image implicitly define the locations of spatial objects, the task at hand might require a more qualitative characterization of the configuration of these objects, say, whether one object will soon occlude another. Handling spatial data is a key task in many applications, including geographic information systems (GISs), meteorological and fluid flow analysis, computer-aided design (CAD) systems, and protein structure databases (figure 1) (Zhao et al. 1999). For example, a GIS system might have large amounts of numeric information about spatial features such as highways and terrain but require query mechanisms to efficiently determine qualitative relationships such as those between a proposed route and wetlands regions.

Qualitative spatial reasoning (QSR) addresses these problems with representational primitives (a spatial “vocabulary”) and inference mechanisms. QSR approaches can be characterized by two important and complementary classes of problems. Problems in the first class are data poor, and the goal is to design representations that can answer qualitative queries without much numeric information. The goal of answering qualitative queries addresses an important aspect of common-sense reasoning by humans and can be found in many practical applications such as computer-aided tutoring or diagram understanding. Because of the lack of detailed numeric information, representations used by the approaches to data-poor problems are often carefully designed by hand with respect to a task at hand. Problems in the second class (for example, scientific and engineering applications from fluid-flow analysis to distributed
Qualitative Spatial Reasoning for Data-Poor Problems

Qualitative reasoning research uses high-level representations of physical systems and domain knowledge for tasks such as prediction, diagnosis, reconfiguration, and tutoring (de Kleer and Brown 1984; Falkenhainer and Forbus 1991; Forbus 1984; Kuipers 1986; Weld and de Kleer 1990) without requiring significant amounts or quality of data. Classical qualitative reasoning work deals primarily with temporal aspects of a system, abstracting away its spatial properties. Following the spirit of this qualitative reasoning research, work in QSR for data-poor domains has focused on similarly “minimalist” spatial representations and inference mechanisms.

Much QSR work has studied purely topological descriptions of spatial regions and their relationships. These approaches often seek to generalize Allen’s temporal interval calculus (for example, a before b, a overlaps b, and so on) (Allen 1983) into higher-dimensional, spatial relationships. One representative approach, the region-connection calculus (RCC) (Cui, Cohn, and Randell 1992), provides predicates for expressing and reasoning about the relationships among topological regions (arbitrarily shaped chunks of space). One version, the RCC-8, provides eight jointly exhaustive and pairwise disjoint predicates (figure 2): (1) disconnected from (DC), (2) externally connected to (EC), (3) partially overlaps (PO), (4, 5) tangential proper part of (TPP and TPPi), (6, 7) nontangential proper part of (NTPP and NTPPı), and (8) identical with (EQ). The axioms specifying these relationships provide rigorous underpinnings to support spatial reasoning. For example, Boolean functions (for example, union, intersection, and difference) allow composition of complex spatial objects (that is, topological shapes). Additional predicates can then test, using theorem proving, topological features of these objects (for example, connect-
Figure 2. The Region-Connection Calculus (RCC) Represents and Manipulates Pairwise Relationships between Regions of Space.
a temporal process changing the “front” between the two regions and ultimately the associated temperatures. This approach is discussed in more detail in the case study section.

Qualitative Spatial Reasoning for Data-Rich Problems

In contrast with the data-poor application domains discussed earlier, many important science and engineering applications are characterized by massive amounts of spatially distributed numeric data (Figure 1). For example, to predict the weather, meteorologists use pressure, temperature, and wind velocity data collected from a large number of spatially distributed weather sensors. Similarly, in designing aircraft with minimal drag, engineers study wind tunnel and simulation data specifying airflow over a body at many points and over many instants of time. In these applications, geometric as well as topological characterizations are necessary; for example, a temperature field is influenced by the geometry of the domain, spatial variations in material property, and boundary conditions.

The massive amount of data, either collected from experiments or produced by simulations, poses significant computational challenges that can be addressed by QSR. In particular, a central problem is the automatic construction of qualitative spatial representations from a given data set to focus the search space for data interpretation and design tasks. QSR approaches to these problems are often built on a sound mathematical theory of geometric and topological analysis, for example, the theory of cell complexes from algebraic topology that naturally defines “closeness,” “composition,” and “abstraction” (Munkres 1984). As discussed earlier, the availability of data provides us the opportunity to automate the construction of qualitative spatial representations. QSR differs from traditional numeric methods for spatial data analysis problems that also abstract numeric data at multiple levels of resolution. For example, engineers use multigrid methods (Briggs 1987) to analyze numeric properties of physical phenomena using a hierarchy of grid discretization. The main difference between QSR and numeric methods lies in the ontological abstraction that QSR adopts. QSR supports more abstract, qualitative reasoning by introducing notions of objects that explicitly encapsulate key spatial properties of a physical domain. For example, meteorologists use abstract structures such as isobars, pressure troughs, and pressure cells to reason about the underlying pressure data at a higher level of abstraction. This key insight—physical properties such as continuity and locality give rise to regions of uniformity in spatially distributed data—enables QSR to overcome the challenge of massive data. In fact, this insight is similar to that underlying the MD/PV approach described in the previous section. Domain-specific physical knowledge justifies the extraction of qualitative information in support of more abstract reasoning processes.

QSR in data-rich domains has many connections and parallels to work in scientific visualization (Rosenblum et al. 1994) and scientific data mining (Ramakrishnan and Graha 2001). For example, weather data can be visualized using pseudocolor to represent temperature, isocontours to connect points of equal pressure, needle diagrams to indicate directions of wind flow with arrows, streamlines to show connected flows, and animations of these to show changes over time. Interactive visualizations allow scientists to explore, focus, filter, project, and transform large data sets. Feature-detection algorithms (for example, for vortexes in fluid data) both identify and track spatial structures over time (Junker and Braunschweig 1995; Ordóñez and Zhao 2000; Samtaney et al. 1994; Yip 1995). Similarly, in scientific data mining, algorithms seek to cluster, generalize, and classify patterns and correlations in databases. For example, mining such patterns can allow identification of general climate patterns across regions (Lu, Han, and Ooi 1993), automatic cataloging of sky images (Fayyad, Weir, and Djorgovski 1993), recognition of volcanoes in images of the surface of Venus (Burl et al. 1994), and tracking of cyclones in weather data (Stolorz et al. 1995).

Spatial Aggregation

Spatial aggregation (Yip and Zhao 1996) is a particular QSR approach for data-massive domains that follows an imagistic reasoning (Yip, Zhao, and Sacks 1995) style, applying vision-like routines to manipulate multilayer geometric and topological structures in spatially distributed data. Thus, it can leverage the connections described earlier with visualization and data mining. In the spirit of qualitative reasoning, however, it focuses on explicit representation and manipulation of objects, explainability of results, and utilization of explicitly encoded domain knowledge. Spatial aggregation is partially motivated by some of the spatial reasoning problems raised by Abelson et al. (1989). The Abelson paper describes a number of approaches to interpreting numeric results of simulations of dynamic systems. These problems often possess a set of geometric and topological
constraints that can be exploited to signifi-
cantly cut down the search space and can be used
to communicate the interpretation results to
human experts. For example, in interpreting
the qualitative behaviors of a nonlinear dy-
namic system, one can describe the set of tra-
jectories that share the same asymptotic be-
haviors as a flow pipe, a geometric object that
can easily be visualized (Yip and Zhao 1996).
Several early examples of using geometric and
and spatial reasoning to aid in scientific computa-
tion include KAM (Yip 1991), which interprets
the behaviors of Hamiltonian systems; MAPS (Zhao 1994),
which designs control laws based on a geometric analysis of the state equa-
tions of a dynamic system; and HIPAIR (Joskow-
icz and Sacks 1991), which analyzes the kine-
matics of fixed-axis mechanisms.

Spatial aggregation organizes computation
around image-like representations of spatially
distributed data (figure 1). In the field ontology,
the input is a field mapping from one contin-
um to another. For example, a two-dimensional
2-D) temperature field associates a temperature
with each point, mapping from \( \mathbb{R}^2 \) to \( \mathbb{R}^1 \); a 2-D fluid field associates a velocity with each point,
mapping from \( \mathbb{R}^2 \) to \( \mathbb{R}^2 \). A field is information
rich in that its representation requires many
bits. The identification of structures in a field
(for example, iso-bars, pressure cells, and fronts)
is a form of data reduction: The data-rich field
representation is abstracted into a more concise
structural representation. For example, a set of
points on a curve can be described more com-
 pactly by a parameterized spline—the spline pa-
thetic parameters are a much more concise represen-
tation than the enumeration of points. Note that
the qualitative physical field approach described
in the previous section starts with an abstract
description of a field (qualitative domain and
range in the field); the synergy between the da-
ta-rich and data-poor fields are explored further
in the case study section.

Spatial aggregation uncovers structures in
fields at multiple levels of abstraction, with
the structures uncovered at one level becom-
ing the input to the structure-discovery pro-
cess at the next level. For example, in a weather
data analysis application (Huang and Zhao
2000), spatial aggregation could extract from
pressure data the isobars, pressure cells, and
pressure troughs. As discussed earlier, contin-
uities in a field give rise to regions of uniformity
that can be abstracted as spatial structures (for
element, isothermal contours are connected
curves of equal [or similar enough] tempera-
ture). Similarly, these structures exhibit their
own continuities; therefore, multilayer struc-
tures arise from continuities in fields at multiple
scales. Spatial objects are introduced as primit-
tives in QSR to encapsulate the geometric and
topological properties of these points, curves,
regions, or volumes. Mathematically, a spatial
object is a cell—a portion of space topologically
equivalent to a ball (Munkres 1984). Adjacency
between the objects is defined by the contiguity
of their cells. Navigating the mapping from field
to abstract description through multiple layers
rather than in one giant step allows the con-
struction of modular programs with manage-
able pieces that can use similar processing tech-
niques at different levels of abstraction. The
multilevel mapping also allows higher-level lay-
ers to use global properties of lower-level objects
as local properties of the higher-level objects.
For example, the average temperature in a re-
gion is a global property when considered with
respect to the temperature data points but a lo-
cal property when considered with respect to a
more abstract region description.

Spatial aggregation provides a set of data
types and operators for constructing the spatial
aggregate hierarchy. The data types and opera-
tors make explicit use of domain-specific
knowledge (figure 3), in particular, the similar-
ity and closeness of both field objects and their
features that are encoded with metrics, adjacen-
cy relations, and equivalence predicates. Yip
and Zhao (1996) present a number of applica-
tion programs, ranging from dynamic systems
analysis to mechanical mechanism analysis, in
terms of the same set of generic operators pa-
rameterized by different such domain knowledge.
The central data type of spatial aggregation, the
neighborhood graph, is an explicit representa-
tion of an object-adjacency relation. The defini-
tion of adjacency is domain specific and de-

deps on the metric properties of the input
field. Common adjacency relations include De-
launay triangulations, minimal spanning trees,
and uniform grids. The neighborhood graph
serves as computational glue, localizing interac-
tions between neighboring objects. The main
SPATIAL AGGREGATION operators aggregate objects
into neighborhood graphs satisfying an adjac-
cy predicate, classify neighboring nodes in-
to equivalences classes with respect to an equi-
valece predicate specifying domain-specific
feature similarity, and redescribe equivalence
classes into higher-level objects with respect to
domain-specific abstraction mechanism. Ad-
ditional operators search through neighbor-
hood graphs, check consistency of objects, ex-
tract geometric properties, and so forth. By
instantiating these operators with proper
knowledge at different levels of abstraction,
spatial aggregation allows specification of a va-
riety of application programs.
very expensive data collection must be carefully planned (for example, for fluid dynamics simulation and aircraft design). In particular, the iterative approach performs spatial analysis of data in one iteration; identifies ambiguities arising in the analysis; and focuses sample selection in the next iteration to clarify the ambiguities, maximizing information content and improving the analysis. This approach has been shown to make highly effective, explainable sampling decisions in several case studies, including discovery of “pockets” in n-dimensional space by aggregation of gradient vector fields in an interpolated representation derived from a minimal number of targeted samples (Bailey-Kellogg and Ramakrishnan 2001); analysis of matrices using a perturbation sampling approach (Ramakrishnan and Bailey-Kellogg 2002) that utilizes consistent correspondence of features to determine properties such as the Jordan form from a small number of samples; and influence-based model decomposition for decentralized control design (Bailey-Kellogg and Ramakrishnan 2001; Bailey-Kellogg and Zhao 2001, 1999, 1998), where locality of a few sampled control effects supports high-quality decomposition of problem domains and reasoning about trade-offs among computation, communication among decentralized controls, and resulting control quality.

Case Study: Reasoning with Weather Data

Consider the approach taken by meteorologists interpreting weather data to make predictions about future conditions. They make sense of large, multicategory data sets by recognizing and explicitly labeling aggregate weather features such as high-low pressure centers, pressure troughs, thermal packings, fronts, and jet streams (figure 4) (Huang and Zhao 2000). They then use weather rules, such as the following, to correlate these features and establish prediction patterns:

1. “Major and minor 500mb troughs are good indicators of existing or potential adverse weather” (Air Weather Service 1975).
2. “At 850mb, the polar front is located parallel to and on the warm side of the thermal packing” (Air Weather Service 1975).
3. “A front lies in a pressure trough and the isobars make an abrupt change in direction at the front” (Blair and Fite 1965).
4. “A front moves slowly when it is nearly parallel to the iso-bars and increases in velocity as the number of iso-bars intersecting it increases” (Blair and Fite 1965).
5. “A strong high east of a low, especially if the
*Primitive Objects* represent locations and structures in spatial data.

Example:

*Compound Objects* combine primitive objects

*Spaces* group objects.

Example (points and curves):

*Fields* associate objects and features.

Example (point $\rightarrow$ temperature):

*Ngraphs* relate nearby objects.

Example (Delaunay triangulation):

*Equivalence classes* group similar objects.

Example (by vector direction):

*Means of Abstraction* connect compound objects at one level of abstraction and primitive objects at the next.

Example (by convex hull):

Table 1. Components of the *Spatial Aggregation Language* (SAL).
standing of distributed parameter fields. The task of modeling such fields is important by itself, for example, in ecology applications where researchers desire to understand interactions among different parameters (for example, shade and temperature profile) (Lundell 1996). As discussed earlier, modeling also leads directly to prediction based on features extracted from a field at one point in time or, even better, the history of such features over time (Ordóñez and Zhao 2000; Yip 1997). Although the weather data application isn’t amenable to control (yet!), modeling is also important when engineers desire to regulate a physical field with some set of controls (Bailey-Kellogg and Zhao 2001), for example, guiding a robotic laser welding arm in response to temperature data from an infrared camera (Doumanidis 1997) or maintaining a uniform temperature profile with a set of concentric circles of heat lamps (Kailath et al. 1996). In the following two subsections, we discuss how data-poor QSR supports reasoning with models of such heat flows and how data-rich QSR supports extraction and manipulation of such models.

Data-Poor Reasoning

This section follows the approach taken by Lundell (1996, 1995) for qualitative physical fields. In reasoning about temperature fields in ecology, dense, precise numeric data and corresponding models are often not available. However, it is desirable to envision qualitative differences in the temporal evolution for a given (qualitative) model. As described earlier, the model is defined in terms of a field—an association of some parameter (here, temperature) with spatial objects in the domain. Composite fields are defined by spatial interactions of fields with overlapping domains and different parameters (for example, temperature and pressure). The static definition of a field’s domain and involved parameters is specified separately from the dynamic process capturing the interactions among the parameters over time. The value of a field parameter belongs to some qualitative space of possible values (such as “warm” or “cold”). At a point in time, the field domain is partitioned into maximal regions of the same value (for example, isothermal regions), which is essentially a place vocabulary (see the earlier discussion of MD/PV). The resulting qualitative spatial representations are then amenable to the general QSR techniques described in the preceding section. In particular, composite fields (for example, temperature and shade) are naturally computable using the intersection of regions in the separate fields. Figure 5 illustrates such qualita-
tive physical fields for the temperature modeling application in both the underlying geometric domain and a diagrammatic representation that captures the relevant topological connectivity and continuity.

Dynamic changes in fields (for example, because of heat flow) are captured with a spatiotemporal extension to the qualitative process theory (Forbus 1984). In particular, spatiotemporal processes are captured as interactions between spatial and temporal processes. In the case study application, each region is warmed by a temporal process that takes into account its irradiation and temperature differences, and the regions of boundaries are adjusted by a spatial process that considers the differences in temperatures. More precisely, the temporal process manipulates variables for heating rate in the regions, with a negative qualitative relationship between the heating rate and the amount of shade (that is, more shade means less heating from the sun) and a monotonic influence between the temperature in the region and the heating rate. The spatial process then distributes heat using flow between adjacent regions of different temperatures. It is specified in terms of an “expansion region” of applicability, starting at the boundary between two regions and spreading at a rate proportional to the temperature difference until equilibrium is reached. Temporal processes within the expansion region cool one part and heat the other. Simulation of this set of processes yields a vision of the qualitatively interesting state transitions in the evolution of a temperature-shade field.

Data-Rich Modeling

This section illustrates that qualitative reasoning about physical fields can extract rich structure from large spatial datasets, in support of tasks such as prediction and analysis. In particular, we focus on the identification of troughs and ridges in weather data. We provide here a high-level discussion of a spatial aggregation–based approach; interested readers are referred to Huang and Zhao (2000) for details about the approach and results.

Troughs and ridges are important features in weather analysis; for example, high-altitude troughs give rise to the bending of jet streams and are important for extended weather forecasts, but surface troughs are useful for locating weather fronts. Trough features are only qualitatively understood (see the sample weather prediction rules at the start of this section); sometimes experts even give different answers about the existence of a trough in a weather map. The key to identifying troughs lies in the qualitative structures of a field of atmospheric pressure data. In particular, the shape and configuration of iso-bars—the iso-contours of the pressure field, collecting points of the same pressure value—indicate areas where troughs are likely present. Visually, troughs and ridges are stacks of iso-bar segments bending sharply and consistently to one direction, with troughs pointing away from lower iso-bars and ridges away from higher iso-bars. Figure 4b shows a trough. Because of the Coriolis force, winds tend to follow iso-bars; so, sharply bending iso-bars indicate sharp change of wind direction, which usually causes more advection; more mixing of warm air with cold air; and therefore, deteriorating weather.

As previously discussed, data-rich QSR focuses on the extraction and manipulation of structures in spatial data. These structures arise as equivalence classes of neighboring objects according to some similarity measure, re-described as primitive objects at a higher level of abstraction for further analysis. A spatial aggregation–based trough-finding algorithm uses

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**Figure 5. Example Qualitative Physical Fields.**
this approach to extract the same qualitative spatial features that experts do—sharply bending segments of iso-curves of pressure data. The input to the algorithm is a gridded pressure data set, and the output is a contoured pressure chart with troughs labeled. In a preprocessing step, iso-bar points are interpolated from the gridded data, yielding a set of “iso-points,” with pressure at specified contour levels. The algorithm then proceeds through two levels of aggregation (see again the section on spatial aggregation for a description of operations in a...
Level 1  At the first level of aggregation, the algorithm groups points into iso-bars.

Aggregate: Build a Delaunay triangulation neighborhood graph for the iso-points. The Delaunay triangulation has a number of important geometric properties. Most importantly here, although the triangulation only acts on iso-points, its edges are “well-behaved” with respect to the aggregated iso-curves, in that its edges connect only points within a single curve or in two topologically adjacent curves.

Classify: Form equivalence classes of neighboring points sharing the same pressure value. At the same time, classify graph edges into strong adjacencies, connecting same-class points, and weak adjacencies, connecting points in different classes.

Redescribe: Abstract each class of same-pressure points into an iso-curve object. As previously discussed, forming a higher-level object allows the computation of aggregate properties; here, curvature is an especially important property. We note that although other algorithms (for example, marching cubes [Lorensen and Cline 1987]) can also be used to contour a pressure data set, the approach taken here yields more structure in the spatial objects, and this structure proves useful in later steps.

Level 2  At level 2, the algorithm groups segments of iso-bars into troughs and ridges.

Filter: Segment the curves and extract high-curvature curve segments. Curve segmentation breaks a curve into piece-wise simple parameterized curves (for example, straight lines or circular arcs); for example, a split-and-merge algorithm (Pavlidis and Horowitz 1974) splits curves at places with high approximation errors and merges segments to avoid oversegmentation. Simple thresholding then allows extraction of high-curvature segments.

Aggregate: Build a neighborhood graph for the high-curvature curve segments based on the between-class (“weak”) adjacencies from level 1. That is, two curves are adjacent if and only if a constituent point in one is adjacent to a constituent point in the other in the original Delaunay triangulation.

Classify: Form equivalence classes of neighboring curve segments that bend in similar directions, within some tolerance.

Redescribe: Abstract equivalence classes of similar-direction high-curvature curve segments into troughs. The abstraction process constructs a curve (for example, B-spline) through the stack of iso-curves (for example, through a representative point on each).

As figure 7 (Huang and Zhao 2000) demonstrates, the results of this algorithm are in qualitative agreement with those of professional meteorologists. Although the expert-drawn trough seems smoother and more visually pleasing, the exact shape and position are not as important for a synoptic map at this scale.
This trough-finding algorithm illustrates the importance of explicitly representing and reasoning with multilevel spatial structures. The edges in a neighborhood graph play two distinct roles in the aggregation process. The classification process in level 1 uses domain-specific knowledge to distinguish these roles as strong and weak adjacencies (figure 8) (Huang and Zhao 2000). Strong adjacencies carry information about the interactions and connections among the constituent parts of an aggregate spatial object and are abstracted as structural information of the object. Weak adjacencies carry information about the interactions and connections between aggregate objects and are abstracted into a higher-level neighborhood graph. Explicitly representing these adjacencies allows the programmer to use a natural encoding of domain knowledge, in terms of equivalence predicates, to identify objects that are internally connected, externally bounded, and related at multiple levels of abstraction.

**Conclusions and Future Research Directions**

We described several representative approaches to data-poor and data-rich problems in QSR. In many applications dealing with spatial data, qualitative spatial representations and inferences are preferable because either detailed numeric information is not available for the domain, or existing numeric methods are unable to describe the kinds of geometric and topological structures in data sets that can help answer high-level spatial queries. As the sample applications demonstrate, QSR is an important aspect of commonsense reasoning and can have a significant impact on many technical and scientific applications.

QSR is a rich problem domain for qualitative reasoning research. To fully realize the potential of QSR, we need to address a number of open research issues. For example, spatial aggregation introduces a number of spatial primitives for describing structures in a data-rich physical field. What are other formulations of the problem, using, say, a primal-dual space representation? What are additional primitives and inference operators in spatial aggregation that might be appropriate? How can probabilistic information be incorporated? An important problem in synthesizing the approaches to data-poor and data-rich problems is to use data-rich approaches to automatically build models for data-poor approaches. Here, the data used to build a model for a data-poor problem could perhaps come from a domain where the physics constraints are similar enough, and

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**Figure 8. Explicit Representation and Aggregation of Spatial Adjacencies.**

A. Neighborhood graph edges are classified into strong (solid) and weak (dashed) adjacencies. B. Strong adjacencies connect internal structure of aggregate objects A, B, and C. C. A higher-level neighborhood graph is constructed from lower-level weak adjacencies between constituent objects.
numeric information is readily available. For example, in an ecology application, although detailed numeric information for a particular region might not be available because of a lack of instrumentation for that region, the model-building process could leverage data from another similar region where sensors have already been deployed.

Although each of the approaches we have described is to some degree based on mathematical theories of topology and geometry, we have yet to develop a rigorous and formal basis for a general theory of qualitative spatial reasoning that can unify the different approaches. Equally important is the development of a set of problem characterizations that can aid in transforming a general theory into an efficient algorithm for a task.

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Note
1. For those interested, the sal source code can be downloaded from www.cs.purdue.edu/homes/cbk/sal.html or www.parc.com/zhao/sal.html.

References


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