Case-Based Reasoning and Spatial Analysis

Alec Holt and George L. Benwell

Abstract: *This paper brings emphasis to the plausible concept of case-based reasoning being integrated with spatial information systems, and the adaptation of artificial intelligence techniques to improve the analytical strength in spatial information systems. This adaptation of artificial intelligence techniques may include examples of expert systems, fuzzy logic, hybrid connection systems and neural networks all integrated with spatial information systems. The unique process of case-based reasoning is described and research into the possible integration of case-based reasoning and spatial information systems is outlined. The benefits of a case-based reasoning spatial information hybrid system are discussed.*

The spatial information and modeling communities recognize that the lack of analytical and modeling functionality is a major deficiency of current spatial information systems (Fischer and Nijkamp 1993; Burrough and Frank 1995). Therefore, there is a perceived need to interface and integrate spatial information systems (SIS) with additional analytical approaches to curtail this deficiency. This has given rise to the notion of intelligent spatial information systems (Leung 1993; Laurini and Thompson 1992), which have adopted some if not all the following statistical and analytical approaches:

1. Expert systems and SIS have been successfully coupled. (Skidmore *et al.* 1991; Fedra 1993; Calori *et al.* 1994; Davis *et al.* 1994; Mason 1994). The architecture of the SIS-expert system link is accomplished and described in many ways. Fedra (op. cit.) describes the levels of integration (trans, embedded and hybrid) and suggests integration is achieved by common files, application generators, common interfaces, shelling and rules. *Linkage by rules* is the most complicated of the above methods of integration and is accomplished by encapsulating knowledge about entities and relationships to variables as rules using a matrix of prior probability. These rules are used by the expert system to link knowledge to the spatial data in a SIS by relating spatial data to pre-defined units. Rules are subjective and this factor makes expert systems a weak AI technique for SIS modeling, especially if the application is modeling an environmental phenomena, then relationships usually can not be expressed with absolute certainty (Skidmore *et al.* 1991).
2. Fuzzy logic (Wang *et al.* 1990; Kollias and Voliotis 1991; Benwell 1993; Davidson 1994) techniques have also been developed for integration with SIS. Fuzzy logic is incorporated into a SIS by representing spatial information as elements, to which membership functions can be applied to produce fuzzy sets. After a fuzzy relational data model is defined, fuzzy techniques can be applied in a SIS environment.
3. More recently, neural networks have been integrated with spatial information systems (De Vel and Muyzenberg 1992; Whitbread 1992; Openshaw 1992; Wyatt and Itami 1994; Skidmore 1995). Many neural network variations exist (that is, from single layer perceptrons to hopfield nets), but the technique most used for integration with SIS is the multilayered feed forward semilinear perceptron which uses the back-propagation algorithm (Skidmore 1995). Spatial data is fed into the net to produce an output and the process is the following: The back-propagation algorithm takes two passes, forward and then backward. In the forward pass, input values are taken and output nodes are calculated. The next pass takes the calculated nodes and compares them with known values, the differences are treated as errors and the errors are used to modify the node weighting. The net is run until the errors decrease to a specified level to produce the final output.
4. Other research directions that further the analytical capability of a SIS include: rule and knowledge-based approaches (Webster 1990; Smith and Yiang 1991; Skidmore *et al.* 1992), hybrid connection systems (Kasabov and Trifonov 1993), multiple criteria decision-making methods (Jankowski 1995) and a more innovative research ap-

Alec Holt is a research assistant in the Department of Information Science at Otago University, and is a member of the university's Spatial Information Research Centre. His current research area is in the coupling of artificial intelligence techniques and spatial information systems to aid alternative analytical processing of spatial data. His research involves an analytical approach called case-based reasoning.

George L. Benwell is an associate professor in the Department of Information Science at Otago University, and director of the university's Spatial Information Research Centre. His main research area is in spatial information systems and system development methodologies, particularly in the modeling of information processes using colored hierarchical Petri Nets.

proach where spatial reasoning is used to identify a given situation with other known typical scenarios (Williams 1995).

As researchers and practitioners further the artificial intelligence cause and with the arrival of object-orientated language, different analytical approaches are being coupled—for example, neural networks with expert systems (Skidmore *et al.* 1992). Case-based reasoning has been coupled with decision-support systems (Burstein 1994). An interesting and important connection lately has been the integration of case-based reasoning and neural networks. The connection method proposes a co-processing hybrid model for classification, by the coupling of case-based reasoning and neural networks (Malek and Labbi 1995).

Therefore, if neural networks and other AI techniques can be successfully integrated with a spatial information system, and if neural networks and other AI techniques can be integrated with case-based reasoning, then case-based reasoning may also be gainfully integrated with a SIS.

Interest in hybrid systems is beneficial because effectual new systems—for example, combinations such as neuro-fuzzy systems—use the strengths of both neural networks and fuzzy systems to provide a more intelligent system. In SIS and modeling communities, these combined advances in AI systems bode well for strengthening the analytical capability of a SIS.

This paper contends that not all AI techniques are currently being fully utilized in the spatial information systems realm. AI usage has tended to be in the classification of image patterns, primarily to complete images and to clean noisy data (Openshaw 1993). Whereas AI techniques should be used to provide better decision support and more intelligent modeling systems. These systems could be used to solve spatial dilemmas, which current spatial information systems fail to do. The family of problems that could be specifically targeted by these systems are problems that require further analytical processing. This paper illustrates an example of using the reasoning of CBR to test spatial sites. This example uses CBR to evaluate test sites with previous spatial sites and amalgamate the spatial similarities of the test and previous sites to provide decision support to solve the spatial dilemma.

Case-Based Reasoning

This paper discusses an additional AI analytical approach called case-based reasoning (CBR). It is envisaged that this approach will further the AI potential usage within SIS by offering its unique features of learning from previous cases. An SIS-CBR hybrid is interesting and important as *similar situations* may require *similar solutions.*

> *The CBR approach can be characterised as relying upon memories of specific experiences rather than upon rules or abstract generalisations. A case-based system does not explicitly know or manipulate many rules and generalizations, but it is able to create generalisations as needed. The generalisations are implicit in the way experience is represented in memory, and in the way the memory selects which cases to supply in support of a particular reasoning task.*
>
> (Owens 1988, p. 302).

Case-based reasoning systems have been designed to address a variety of task orientations including diagnostic reasoning, adaptive planning, hypothesis generation, explanation, adversarial reasoning, analogical reasoning and hypothetical reasoning. Traditionally, CBR techniques are invoked when a domain is characterised by unclear problems as much as having unclear answers. When a *novel* problem is encountered, a case base of previous problems and solutions is consulted to determine what experiences are relevant to the current situation. Solutions from more than one case may be merged to address the current problem, and multiple solutions are typically generated with an assessment of their respective strengths. When the novel problem is solved, it can be added to the case base. This retaining function enables CBR systems to learn from previous experiences (Bradtke 1988; Hammond 1988; Kolodner 1987).

The following example, while not spatial in its context, provides a simple illustration of how a case-based reasoning system can be used as a problem resolver. The example is concerned with printer problems. The user begins by typing in a description of the problem. For example: *my printer outputs white streaks* and then the initial search results are displayed (5 of 96 cases were selected):

100	ink cartridge low on toner causes white streaks,
73	ink cartridge low on toner causes faded print area,
55	using bad transparency stock,
45	printing on the wrong side of the paper,
44	ink cartridge is damaged causing black streaks.

Further questions can be answered by the user to narrow the search:

are you printing on transparencies?
are you printing on the correct side of the paper?
does cleaning the printer with cleaning paper remove problem?

The cases are displayed with a number indicating the percentage of the number of attributes in the retrieved case that match the research criteria, and ranked in ascending order of the highest number. The user can then click on the case (*100 Ink cartridge low on toner causes white streaks*) and a picture with instructions of how to re-install the toner is displayed.

The Case-Based Reasoning Cycle

The framework for describing case-based reasoning in this paper is first with a cycle, and then by methods. In general, a CBR cycle (Figure 1) may be described by the following four processes (Aamodt and Plaza 1994):

1. **retrieve** the most similar case(s),
2. **reuse** the information and knowledge in that case to solve the problem,
3. **revise** the proposed solution,
4. **retain** the parts of this experience likely to be useful for future problem solving.

Figure 1 illustrates a simple spatial example to portray the CBR cycle. The example identifies an unknown spatial phenomena as the South Island which is calculated from the case of the spatial phenomena of New Zealand. A new problem is solved by retrieving one or more previously experienced cases, reusing the case, revising the solution based on reusing a previous case, and retaining the new experience by incorporating it into the existing case-base. Of the four processes, each involves several more specific steps (Figure 2). An initial description of a problem defines a new case. This new case is used to *retrieve* a case from the collection of previous cases. The retrieved case is combined with the new case—through *reuse* into a solved case (that is, a proposed solution to the initial problem). Through the *revise* process, this solution is tested for success, for example, by being applied to the real-world environment or evaluated by an expert, and repaired if failed. During *retain*, useful experience is retained for future reuse, and the case base is updated by a new learned case, or by modification of some existing cases.

As indicated in the process view, general knowledge usually plays a part in the cycle by supporting the CBR processes. General knowledge means general domain-dependent knowledge, as opposed to specific knowledge embodied by cases. In Figure 1, the example identifies an unknown spatial phenomena as the South Island, which is calculated from the general knowledge and case of the spatial phenomena of New Zealand. The process view briefly described emphasizes that CBR is a cycle of steps. To decompose further and describe the four top-level steps, a task-oriented view is used where each step, or subprocess, is viewed as a task that the CBR reasoner has to achieve. While a process-oriented

FIGURE 1. The case-based reasoning cycle. (Adapted from Aamodt et al., AICom, Vol. 7 No. 1).

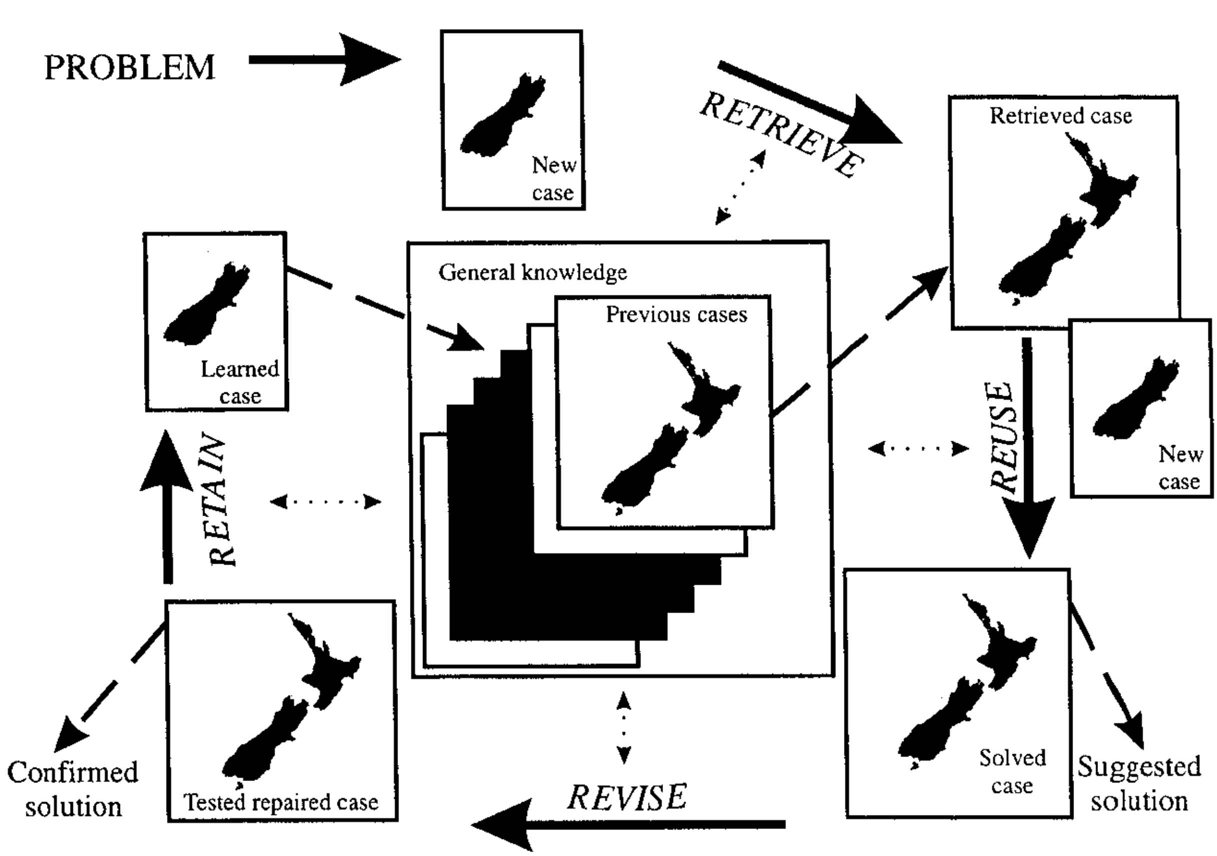
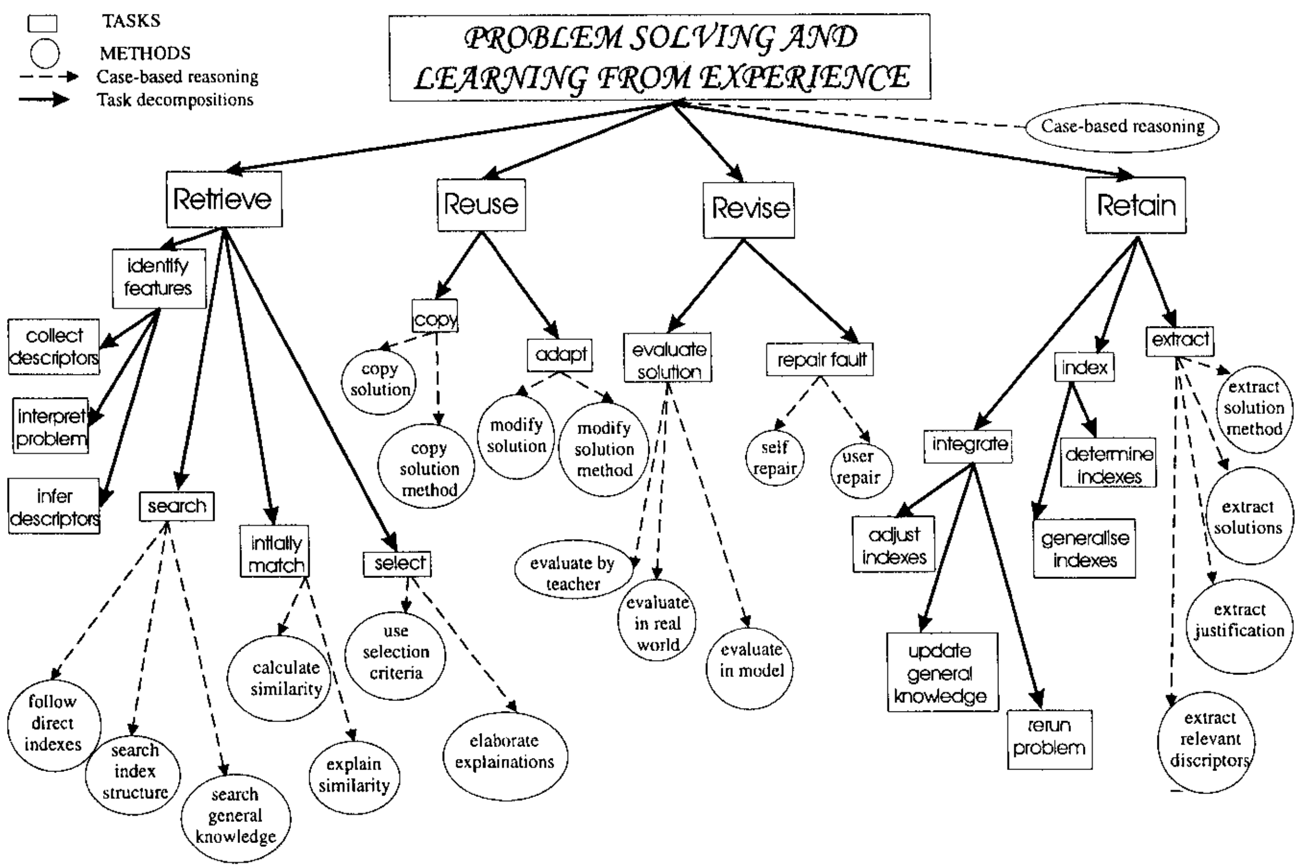


FIGURE 2. A task-method decomposition of case-based reasoning. (Adapted from Aamodt and Plaza, AICom, Vol. 7 No. 1).



view enables a global, external view of what is happening, a task-oriented view is suitable for describing the detailed mechanisms from the perspective of the CBR reasoner itself.

The task-method structure (Figure 2) is shown in the task orientation view (Aamodt and Plaza 1994). The top-level task is problem solving, and learning from experience and the method to accomplish the task is case-based reasoning. This decomposes the top-level task into the four major CBR tasks corresponding to the four processes of Figure 1: retrieve, reuse, revise, and retain. All four tasks are necessary to perform the top-level task. The retrieve task is partitioned in the same manner (by a retrieval method) into the tasks, identify (relevant descriptors), search (to find a set of past cases), initial match (the relevant descriptors to past cases), and select (the most similar case). At this level of description all task partitions in the task orientation view are complete; that is, the set of subtasks of task are intended to be sufficient to accomplish the task. In the task-orientation view no control structure exists over the subtasks, although a rough sequencing is implied by having put earlier subtasks higher up in the figure then those that follow. The control is specified as part of the problem-solving method. The relations between tasks and methods identify alternative methods applicable for solving a task. A method specifies the algorithm that identifies and controls the execution of subtasks, accesses and uses the knowledge and information needed to do this. The methods shown are high-level method classes, from which one or more specific methods are chosen. The method set as shown is incomplete, that is, one method shown may be sufficient to solve the task, several methods may be combined, or other methods that can do the assignment. The methods shown in Figure 2 are task decomposition and control methods. At the bottom level of the task hierarchy, a task is solved directly, that is, by the (what may be called) task-execution methods.

CBR Methods

The challenge for CBR is to produce methods suited for problem solving and learning—in particular, subject domains and for particular application environments. As with AI, no universal CBR methods exist which are suitable for every domain of application. A case-based reasoning approach is heavily dependent on the structure and content of its collection of cases (case memory). Since a new case is solved by recalling a previous experience (suitable for solving the new case) the case search and matching processes need to be both effective and time efficient. Since the experience (from a case solved) has to be retained, these requirements also apply to the method of integrating a new case into the memory.

Representation in CBR is primarily the problem of deciding what to store in a case, finding an appropriate structure for describing case contents, and deciding how the case memory should be organized and indexed for effective retrieval and reuse. An additional problem is how to integrate the case memory structure into a model of general domain knowledge, to the extent that such knowledge is incorporated.

Representation Methods

Representation in CBR is primarily the problem of deciding what to store in a case, finding an appropriate structure for describing case contents, and deciding how the case memory should be organized and indexed for effective retrieval and reuse. An additional problem is how to integrate the case memory structure into a model of general domain knowledge, to the extent that such knowledge is incorporated.

Retrieval Methods

The *retrieve* task starts with a new case description, and ends when a best matching previous case has been found. Its subtasks are called identify features, initially match, search, and select-executed in that order. The identification task produces a set of relevant problem descriptors, the goal of the matching task is to return a set of cases sufficiently similar to the new case (given a similarity threshold of some kind), and the selection task works on this set of cases and chooses the best match. Some case-based approaches retrieve a previous case based on superficial, syntactical similarities among problem descriptors, while other approaches retrieve cases based on features that have deeper, semantic similarities. To match cases based on semantic similarities and relative importance of features, an extensive body of general domain knowledge is needed to produce an explanation of why two cases match and how strong the match is. Syntactic similarity assessment (a knowledge-poor approach) has its advantage in domains where general domain knowledge is difficult or impossible to acquire. Conversely, semantic-oriented approaches (knowledge-intensive) can use the contextual meaning of a problem description in its matching, for domains where general domain knowledge is available (Aamodt *et al.* 1994).

Reuse Methods

The *reuse* of the retrieved case solution in the context of the new case focuses on two aspects:

- the differences among the past and the current case, and
- what part of a retrieved case can be transferred to the new case?

The possible two subtasks of reuse are Copy and Adapt:

Copy: In simple classification tasks the differences are abstracted away and the solution class of the retrieved case is transferred to the new case as its solution class. (Riesbeck *et al.* in Malek *et al.* 1995).

Adapt: There are two main ways to adapt past cases: reuse the past case solution (transformational use) and reuse the past method that constructed the solution (derivational reuse). In transformational reuse, the past case solution is not directly a solution for that new problem but there exists some knowledge in the form of transformational operators such that when applied to the old solution they transform it to the new solution for the new case. Derivational reuse looks at how the problem was solved in the retrieved case. The retrieved case holds information about the method used for solving the retrieved problem. Now derivational reuse reinstantiates the retrieved method to the new case and replays the old plan in the new context (Malek *et al.* 1995).

Revise Methods

This phase consists of evaluating the case solution generated by the reuse phase. If successful, learn from the success, otherwise *repair* the case solution using domain-specific or user knowledge (Aamodt and Plaza 1994). The evaluation task takes the result from applying the solution in a real environment. Case repair involves detecting the errors of the current solution and retrieving or generating explanations for them. The repair module possesses general casual knowledge and domain knowledge about how to disable or compensate causes of errors in the domain. The revised case can then be retained or it can be evaluated and repaired again (Malek and Labbi 1995).

Retain Methods

Case *retainment* is the process of incorporating what is useful to retain from the new case-solving episode into the existing knowledge. The learning from success, or failure, of the proposed solution is triggered by the outcome of the evaluation and possible repair. Learning involves selecting which information from the case to retain, in what form to retain it, how to index the case for later retrieval from similar cases, and how to integrate the new case in the memory structure.

The Proposed CBR-SIS Hybrid

The following are examples of CBR applications which retrieve, revise, reuse and retain spatial data:

Roentgen is a case-based system which aids in planning radiation therapy for new patients based on geometrically similar patients. Geometric similarity is computed by the polygons contained in each patient's case. The polygons define the outline of each tissue (body outline, lungs, spinal cord) in the cross-section for the case. For each tissue, a corresponding list of coordinates exists that defines a polygon representing the tissue. In order for the retriever to determine accurately similarities between patient geometrics, Roentgen uses features derived from ellipsized patients, that is, previous patients' cases that have had their geometrics stored mathematically. These features from ellipsized patients are idealised versions of the new patient and the patients in memory. The ellipsized patient is obtained by approximating each tissue in the patient's cross-section with Roentgen's best-fit ellipse. Once the ellipsized patient has been computed, the system computes the following features, area, eccentricity, orientation, rho (the distance from the target centroid[3] to the centroid of the ellipse of the tissue), theta (the angle formed by the vector from the target centroid to the tissue centroid with the positive x-axis). These features aid in finding a similar patient case. The geometrically similar feature is only one part of the Roentgen system but it describes a spatial method of defining cases to be retrieved (Berger 1992).

Another case-base uses spatial data to reason with historical meteorological data. The case-base consists of meteorological data for past weather situations and index labels describing the key features of each situation. Numeric data are arranged in a grid for the following features: pressure, temperature, humidity, wind speed, wind direction and relative vorticity. Queries are constructed using graphical objects such as points, vectors and regions that denote meteorological features. These features are described as three types:

1. static—describe meteorological phenomina at points in time,
2. dynamic—displaying features as they vary over time,
3. relational—encoding spatial constraints between features.

Corresponding to each graphical object in a query, there is an underlining symbolic representation that is used in a case retrieval. Index labels are also constructed using the same representation vocabulary (Jones and Royhouse 1993). Interestingly, other retrieval methods such as, pattern recognition algorithms, indexes (Johnsson 1995), fuzzy retrieval (Kollias *et al.* 1991) and spatial templates (Williams 1995) have been integrated with spatial information systems (Johnsson 1995; Williams 1995; Kollias *et al.* 1991). CBR makes use of a retrieval system but also incorporates other processes, namely: reuse, revise and retain. Therefore this paper suggests that a CBR-SIS hybrid has the potential to increase the analytical power and functionality of a SIS and should not be overlooked.

The Perceived Benefits of a SIS-CBR Hybrid

The authors suggest that initially a SIS-CBR hybrid could be used to help make spatial decisions, and subsequently to make a SIS more intelligent by increasing the analytical functionality and providing learning facilities. It is also suggested that ultimately, CBR will improve the ability of a SIS to be used for decision support and to ameliorate its spatial analysis techniques. For example, CBR could be used as a tool for spatial diagnosis by:

- having a user-help system for quantifying spatial phenomena, where the user types in the spatial criteria of the problem and a similar spatial case is retrieved and possibilities to classify or solve the problem are suggested,
- making simulation possible, which is useful for estimation and prediction of spatial phenomena, and
- providing new opportunities in spatial analysis via information retrieval and pattern recognition.

Two examples demonstrate some benefits; the examples use SIS and CBR functionality and highlight the interactive potential provided by combining SIS with CBR.

Example 1

The SIS-CBR hybrid is used *to facilitate searches* and answer the following questions:

- Are there any other spatial phenomena such as this?
- If so, what attributes are associated with those phenomena?

In finding a similar spatial pattern a SIS is needed to display and store the data, and CBR provides the functionality to find the similar pattern and more importantly to analyze the properties of the similar pattern that is found. These properties would extend from the obvious spatial pattern to other attributes associated with that spatial pattern. This type of functionality could be used for classification or to solve more complex problems using previous experiences.

This is an example of a *search to find a similar spatial pattern(s)*; the following headings-problem, retrieve, reuse, revise and retain indicate the CBR processes.

Problem: Typically users may need to know more about a spatial phenomena, before they make a decision concerning the spatial phenomena. Knowing what has been done in similar cases with a similar spatial phenomena can aid the decision-maker/problem-solver (Figure 3).

FIGURE 3. The searched spatial phenomena.

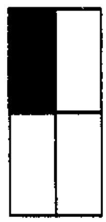


FIGURE 4. The case-base.

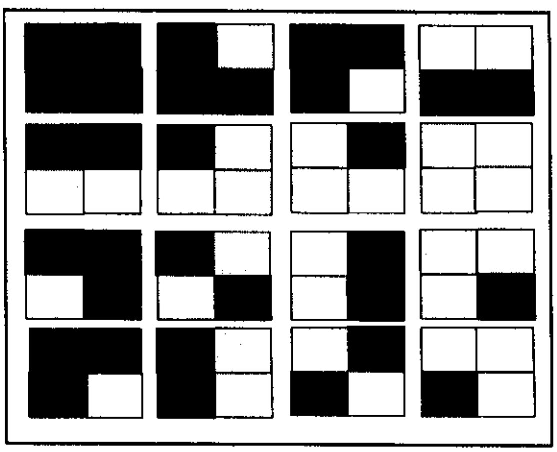


FIGURE 5. The similar spatial phenomena.

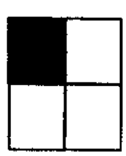
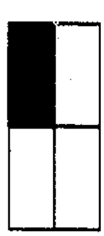


FIGURE 6. The revised and retained spatial phenomena.



Retrieve: CBR enables the user to search the case-base to locate other spatial phenomena with a similar pattern (Figure 4).
Reuse: A case is found which has a similar pattern to the searched spatial phenomena and the case has attributes associated with a previous spatial phenomena (Figure 5).
Revise: A decision is made by the user concerning the searched spatial phenomena, based on the similar spatial phenomena (Figure 6).
Retain: The user then has the option to retain or discard the searched spatial case. If the case is retained, then the searched spatial case, the decision choice, plus other attributes are encapsulated to form a new case in the case-base (Figure 6).

Example 2

The SIS-CBR hybrid is used *to facilitate queries* and answer the following questions:

- Which spatial phenomena have the following criteria?
- What attributes are associated with a spatial phenomena with these criteria?

These criteria have spatial properties and the benefit of using a SIS for selecting slope, height and aspect is the ease of interpreting, manipluating and representing spatial data. The benefit of using a fully integrated SIS-CBR hybrid would be the ability to enter spatial data directly from digital maps and digital terrain models directly into a CBR. Once the data are entered, the select action tries to find a similar case; the similar case is then displayed with any associated attributes. CBR provides the unique function of allowing further information related to the similar case to be used. This data can be saved as a new case if a decision is made based on previous cases—CBR's learning ability.

This is an example of *querying a spatial phenomena to find similar spatial cases which suit a set of criteria.* The spatial cases are derived from a spatial database designed to manage and conserve a mainland breeding Royal Albatross colony (Purvis *et al.* 1993). This colony has been mapped using measurements from both field surveying and global positioning systems technology. This information has been used to create a digital terrain model which in turn has been used to generate slope and aspect analysis (McLennan *et al.* 1994). Slope analysis is an important factor in determining which sites the albatrosses prefer (Mills 1990). Historical data are available on previous nest sites. The test is to find, given a new case, sites that are a close match to other successful nest sites. The match would be primarily determined from previous cases which were suitable for nesting based solely on topographical information. While this match does not necessarily reflect the full case history of dependant variables it serves as a good instructive example. The example is to clearly illustrate CBR, and in no way should be interpreted as a definitive statement on Albatross nesting preferences.

This *query* example has a case definition much more detailed than the previous *search* example.

For the albatross case file, blocks of code were written to define the following: introduction, case definition, index definition, modification index, weight rule definition, repair rule definition and case instance.

An example of a case definition for the albatross case file is:

```
field slope type is (low, moderate, high);
field aspect type is (north, east, south, west);
field view type is (yes, no) weight is 1;
field on_track type is (yes, no) weight is 2;
field height type is number weight is 0;~m
field coordinate_x type is number weight is 0;
field coordinate_y type is number weight is 0;
end;
```

The CBR program CASPIAN was used to run this application. In the case definition above, spatial properties are defined as fields in the case file. The case definition was used as a mechanism to process the spatial data input and the case instance was searched to fulfill the criteria of the case definition. Once a similar case instance was found, it was possible to locate the similar case instance based on the fields of the case instance. Once these similar cases are located they can then be displayed and the user has the option to add the similar case to the casebase memory, hence showing the benefit of a CBR to a SIS by increasing the analytical and learning functionality of a SIS.

Both examples were conducted using loose coupling, but it is envisaged that the SIS-CBR hybrid will become fully integrated in time. Loose coupling was done by passing data from the SIS into another package by editing the ASCII output file produced by the SIS. This is one of the approaches used for coupling spatial data analysis with a SIS, for example the approach was used in which output from ODYSSEY is passed to GLIM (Gatrell 1987).

Conclusion

This paper has suggested the probable use of CBR applications for help-desk applications. This proposed CBR-SIS hybrid will promote the coupling of CBR to spatial information systems. The use of cases for human browsing and decision-making is likely to lead to an increased interest in intelligent computer-aided learning, training and teaching. The strong role of user interaction, of flexible user control, and the drive toward interactiveness of systems favors a case-based approach to intelligent computer assistance, since CBR systems can continually learn from, and evolve through, the capturing and retainment of past experiences. This paper also illustrates the potential of computational reasoning in the spatial realm to recognize sets of patterns, predict, provide decision support and simulate spatial phenomena. That is, to recognize situations and train data to give spatial solutions to spatial problems. This paper has ultimately tried to demonstrate that SIS would benefit from a CBR link.

Future research will be directed at experimenting with SIS functionality in the CBR realm:

- To further develop the SIS component by increasing the integration level with the SIS-CBR hybrid, which at the moment is achieved by loose coupling. Ultimately the hybrid should be fully integrated, to provide a generic tool for many environmental and spatial applications. For example, if a user has queried a data set and found a microclimate, which has conditions that suit the pinot noir grape variey, the user can then search for a similar area without having to go through the series of steps involved in selecting the first microclimate. This has significant potential for habitat analysis of wildlife.
- Test CBR criteria and results against other techniques with the same data set.
- Applying Kridging to spatial cases to find variables to quantify spatial similarities of similar spatial cases.

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