Case-Based Reasoning for Eliciting the Evolution of Geospatial Objects

Joice Mota†, Gilberto Camara*†, Maria Isabel Escada†, Olga Bittencourt †, Leila Fonseca, and Lúbia Vinhas†

[1] INPE – National Institute for Space Research,
Av dos Astronautas 1758,
12227-001 São José dos Campos, Brazil
{joice, gilberto, isabel, olga, leila, lubia} @dpi.inpe.br

Abstract. This paper proposes an automated approach for describing how geospatial objects evolve. We consider geospatial objects whose boundaries and properties change in the time, and refer to them as *evolving objects*. Our approach is to provide a set of rules that describe how objects change, referred to as *rule-based evolution*. We consider the case where we have a series of snapshots, each of which contains the status of the objects at a given time. Given this data, we would like to extract the rules that describe how these objects changed. We use the technique of case-based reasoning (CBR) to extract the rules of object evolution, given a few representatives examples. The resulting rules are used to elicit the full history of all changes in these objects. This allows finding out how objects evolved, recovering their history. As an example of our proposed approach, we include a case study of how deforestation evolves in Brazilian Amazonia Tropical Forest.

Keywords: Spatio-temporal data, evolving objects, Case-Based Reasoning.

1 Introduction

The computational modelling of geospatial information continues to be, after decades of research, a challenging problem which defies a definitive solution. Since computer models assign human-conceived geographical entities to data types, matching geospatial data to types and classes has been the focus of intense research. Recently, there has been much interest on modelling and representation of geospatial objects whose properties change [1-5]. Such interest has a strong practical motivation. A new generation of mobile devices has enabled new forms of communication and spatial information processing. Remote sensing data is becoming widespread, and more and more images are available to describe changes in the landscape. As new data sources grow, we are overwhelmed with streams of data that provide information about change.

Representing *change* in a GIS is not only an issue of handling time-varying data. It also concerns how objects gain or lose their identity, how their properties change, what changes happen simultaneously, and what causes change. We consider that finding a unique comprehensive theory for spatio-temporal data types and operators is arguably an unsolvable problem. This irremovable complexity is a direct outcome of the ambiguities for defining 'time'. Time can be viewed as an independent entity of the universe, a dimension in which events occur in sequence. That is the view subscribed by Newton and used in the tradition of experimental physics. A second view is to consider time as an intellectual construct within which humans sequence and compare events. This second view is the tradition of Leibniz and Kant. These two opposing views lead to the controversy in the philosophy of time over whether extension in time is analogous to extension in space, the so-called 3D/4D controversy [6]. For a further philosophical discussion of spatio-temporal concepts, see [1] [3] [4]. Therefore, we need practical solutions that handle specific problems. We need first to find out the needs and constrains of the application domain and then choose a suitable approach, from the many available scientific proposals.

As Goodchild et al.[5] point out, the distinction between geospatial entities as continuous fields or discrete objects also applies in the temporal domain. In this paper, we deal with computational models for time-varying discrete geospatial entities. We refer to those as *geospatial objects* and distinguish two broad categories. The first category concerns objects whose position and extent change continuously, referred to as *moving objects*. The second type concerns objects bound to specific locations, but whose geometry, topology and properties change but at least part of its position is not altered. We refer to these as *evolving objects*, which arise in urban cadastre and in land cover change. For an alternative characterization of spatio-temporal objects, see Goodchild et al.[5].

This paper describes a computational model for *evolving objects*, which tracks changes that occurred during an object's lifetime. The proposed model aims to answer questions such as *"What changes took place for each object?", "When did these changes occur?"*, and "*How did the changes take place?*". We aim to extract the history of an object from its creation to its disappearance, including references to other objects involved. Eliciting the history of each object helps us to understand the underlying causes of change. To be able to record the complete history of each object, we need a model that uses previous cases as well as knowledge elicited from an expert as the main sources of knowledge used to solve new problems. This leads to the subject of this paper. We propose a computational method that contains a set of rules that describe how *geospatial objects* evolve, based on a sample of existing cases. These rules arise from knowledge about the application domain. Using these rules, we can extract a detailed history of the objects and track their evolution. Our proposal applies the Case-Based Reasoning (CBR) technique to set up the evolutionary rules, defining a set of types for objects and a set of constraints applicable on those types.

In what follows, we review previous work on section 2 and describe our proposal in Section 3. In section 4, we describe an experiment where we applied our method to a spatio-temporal study of deforestation evolution. This paper builds on previous work by the authors [7-9]

2 Challenges in describing how spatial objects evolve

In this section, we consider previous work on models for evolving objects and introduce the challenges in describing how these objects change. Evolving objects are typical of cadastral and land change applications. Computational models for describing such objects are also referred to as *lifeline models*. Lifeline models use three ideas: *identity*, *life*, and *genealogy*. Identity is the characteristic that distinguishes each object during all its life. Life is the time period from the object's creation until its elimination. Genealogy implies managing the changes that an object has during its life. Hornsby and Egenhofer [10] stress the need to preserve an object's identity when its geometry, topology, or attributes change, a view supported by Grenon and Smith [3]. Consider the case of parcels in an urban cadastre. A parcel can change its owner, be merged with another, or split into two. A possible approach is to describe an object's history based on operations such as creation, splitting and merging [10, 11]. However, these authors do not consider the problem of extracting the evolution rules from the objects themselves. They also only consider objects of a single type. In this paper, we consider objects of different types and we provide ways to extract their evolution rules.

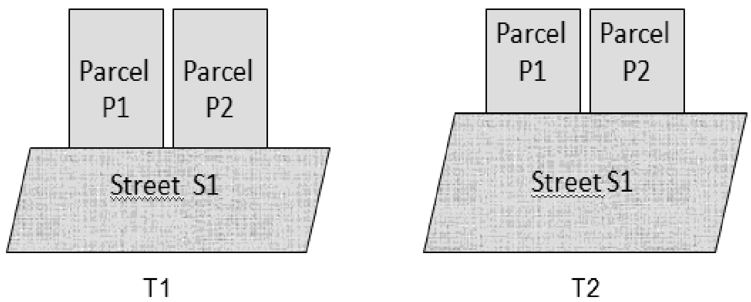


Fig. 1 – Example of object evolution

To take a simple motivational example, consider Figure 1, where there are three objects: S1 of type *'Street'* and P1 and P2 of type *'Parcel'*. *Given the geometries of these objects at times T1 and T2, how can we find out how these objects evolved?* To model this example, we need to consider different rules for spatial operations. Consider the case of the '*merge*' geometric operation, which joins the geometries of two objects. When the objects have different types, merging two objects can produce different results. When the object types are '*Street*' and '*Parcel'*, there should be different rules for the result of the merging two objects. One possible set of rules is: (a) "merging two *Parcels* results in a *Parcel*"; (b) "merging a *Street* with a *Parcel* results in expanding the *Street"*.

As a second example, consider how the internal and external borders of Brazil changed, as shown in Figure 2. Each polygon in Figure 2 is a Brazilian state. The

Brazilian borders have changed significantly since the 18th Century, both because of internal division (creation of new states from existing ones) and inclusion of external areas (through international treaties). Suppose we want to devise a procedure that, given the snapshots shown in Figure 2, tries to extract the history of Brazil´s internal and external borders. Such a method would have to distinguish at least three data types (*'Country'*, *'State'*, *'ExternalArea'*) and would need a set of type-dependent rules for object merging and splitting. As a first guess, this set would have these rules:

R1. Splitting an existing State produces two States: a new State and the existing State with a smaller area.
R2. An existing State can be converted into a new State with the same borders.
R3. Merging a State with an existing State produces a State with lager area. The new area is assigned to an existing State.
R4. Merging a Country with an External Area produces a Country with larger area. The new area is assigned to an existing State.
R5. Splitting a State from a Country produces a Country with smaller area and a new part of the External Area.

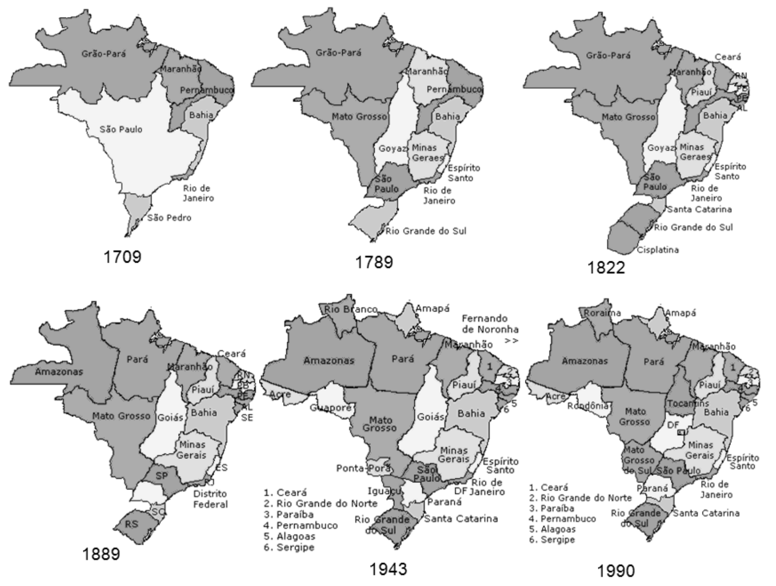


Fig. 2 – Evolution of internal and external borders of Brazil from 1709 to 1990.

These rules are not the only possible set. They may be able to rebuild a believable history of the Brazilian states, but may fail to be historically accurate. Given a set of snapshots which show that state of spatial objects in different times, we are not always able to remake their precise history. However, often the snapshots are all we have, and we need to devise ways to make a likely guess about the objects' evolution.

These examples and similar cases lead us to propose the idea of *rule-based evolution of typed geospatial objects*. Our view of types comes from Computer Science, where types are tools for expressing abstractions in a computer language

[12]. On a theoretical level, a type is a set of elements in a mathematical domain that satisfy certain restrictions. A *typed object* is an object whose evolution is subject to constraints that are specific to its type. Thus, in the Brazilian borders example, objects of type '*Country*' and those of type '*State'* use different rules to describe their evolution. Models where objects have different types and evolution cases are richer and more powerful than typeless ones.

3. Extracting the Evolution Rules using Case-Based Reasoning

In this section, we describe the use of Case-Based Reasoning (CBR) to extract the evolution rules for a set of geospatial objects. CBR is a method for problem solving that relies on previously used solutions to solve similar problems [13]. In contrast to techniques that rely solely on *general* knowledge of a problem domain, CBR is able to use the *specific* knowledge of previously experienced, concrete problems [14]. This is a recurring technique in human-problem solving. To solve a new problem, we recall how we handled a similar one in the past and try to reuse it. A new problem is solved by finding a similar past case and reusing it in the new problem. CBR is an incremental technique, since experience learned in a case is applied for solving future problems.

Traditional rule-based inferences have no memory of previous cases, and use the same set of rules for solving all problems. Instead of doing inferences using a large group of rules, a CBR-based software keeps track of previous cases. When confronted with a new problem, it tries to adapt rules that were useful in similar cases, thus increasing continually its knowledge base [14]. The similarity between two problems can often ensure the interpretation adopted for a previous case can also adopted for the new one.

There are two types of CBR implementations: automatic procedures and information recovery methods [13]. Automatic systems solve the problem in an autonomous way and provide methods to evaluate the results of their decisions. Information recovery methods use human experts to set up the problem-solving rules based on well-known examples. These rules are then used to perform the desired task. The current work uses a CBR software of the second type. Following [14], our proposed CBR technique has the following main steps: 1) Select a set of exemplary cases in the database; 2) Use these cases to set up a set of evolution rules with the help of a domain expert; 3) Test the proposed solution and, if necessary, revise it; and 4) Store the experience represented in the current set of rules for future reuse. The steps to model and to represent how spatio-temporal objects evolve (shown in Figure 3) are:

1. *Retrieval of snapshots of the area that contains a set of geospatial objects whose history we want to describe.*
2. *Select a subset of this data that allows the human expert to find out the different types of geospatial objects and set up their evolution rules.*

3. *Represent these evolution rules using CBR.*
4. *Recover all objects from the database and compute their history based on the evolution rules.*

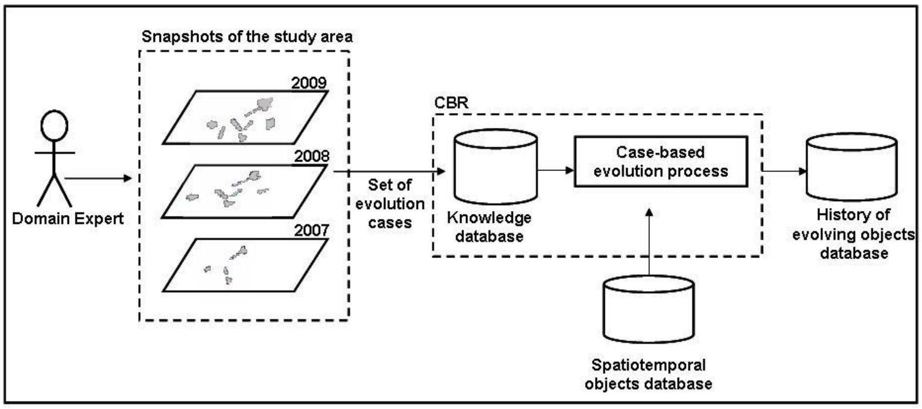


Fig. 3. General view of CBR method for eliciting geospatial objects evolution.

The domain expert defines two types of rules for defining the objects' evolution: *description rules* and *evolution rules*. The *description rules* define the types of geospatial objects. The *progression rules* define how objects evolve under spatial operations such as *'split'* and *'merge'*. The expert defines the *description rules* considering the objects' properties and their spatial relationships, including topological predicates such as *'cross'*, *'close to'* and *'touch'*. Consider Figure 4, where some prototypical land change objects are portrayed. Figure 4(a) shows three objects at time T1. At time T2, three new objects appear as shown in Figure 4(b). After application of the description and progression rules described below, the resulting objects are shown in Figure 4(c).

In this case, the description rules define the existence of three types of objects: *Large Geometric (LG), Linear (LIN)* and *Small Geometric (SG),* according to the following rules:

DR1. An object with perimeter/area ratio smaller than 50 is a Linear object.
DR2. An object with perimeter/area ratio greater than 50 and whose area is less than 10 hectares is a Small Geometric object.
DR3. An object with perimeter/area ratio greater than 50 and whose area is more than 10 hectares is a Large Geometric object.

These rules allow us to identify the objects in Figure 4, as shown in the labels assigned to each object. For this case, a possible set of evolution rules would be:

ER1. A Small Geometric object that touches a Large Geometric object is merged with the Large Geometric object.
ER2. Two adjacent Small Geometric objects are merged.
ER3. Two Linear objects that are adjacent are not merged.

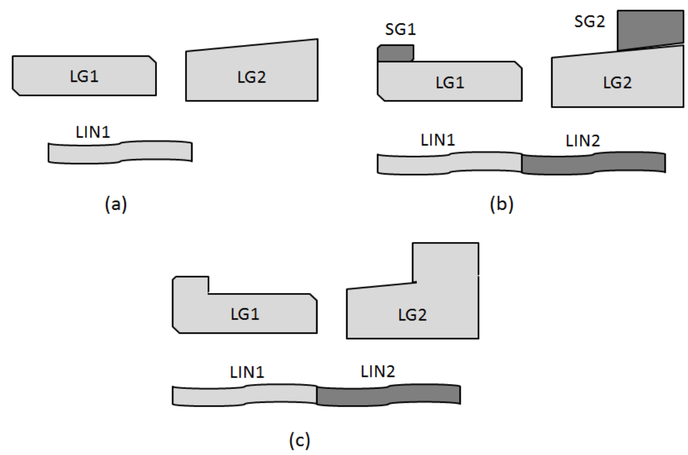


Fig. 4 – Evolution of prototypical land change objects: (a) Time T1; (b) Time T2 before application of evolution rules; (c) Time T2 after application of evolution rules.

Applying these rules, the *Small Geometric* objects shown in Figure 4(b) are merged with the adjacent *Large Geometric* objects, thus resulting in a spatial expansion of the latter objects. This example shows the need for a software organization that is able to represent the *description* and *evolution rules* and apply them to extract the history of a set of objects. We describe this organization is in the next section.

4. CBR-based Geospatial Object History Extractor

This section describes the architecture of the geospatial history extractor that uses CBR (Case-based reasoning). A CBR software stores knowledge as a set of cases. Each case contains data about a specific episode, with its description and the context it can be used [15]. The contents of each case include a set of rules set up by the domain expert. Among the several existent techniques for knowledge acquisition for CBR [16], we used unstructured interviews, where the information is obtained through direct conversation with the specialist. In these interviews, he gives his perspective of the problem, and a computer specialist records these cases. The expert elicits the knowledge domain in two steps. First, he describes the objects in their environment (*description rules*). Second, he analyses thes outcome of spatial operations between the objects (*evolution rules*). After the expert produces the rules, the CBR software stores a set of rules for each case, as shown in Figure 5.

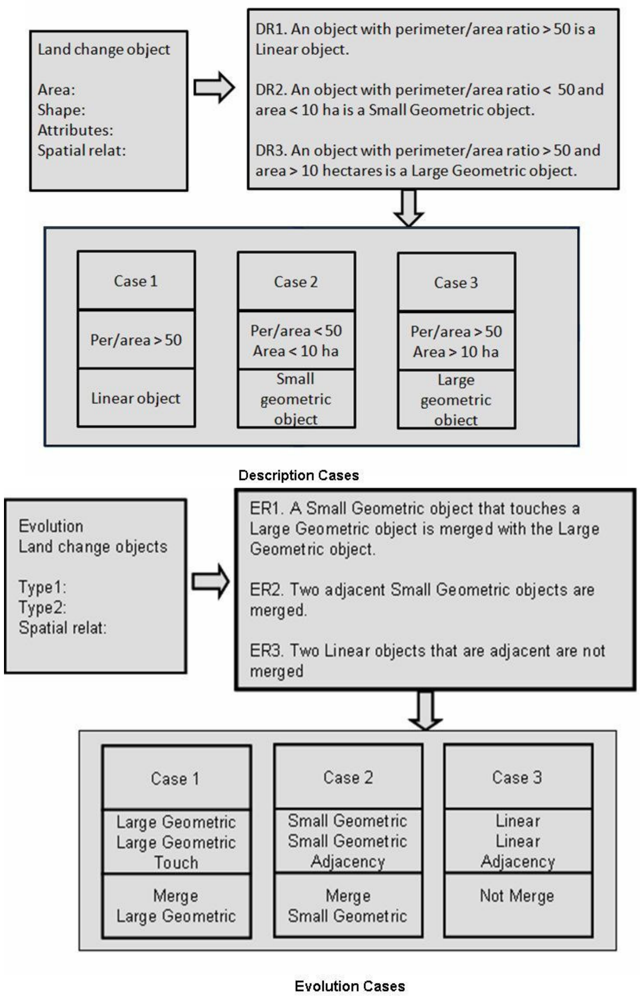


Fig. 5 – Example of case construction based on expert rules

The knowledge base consists of a series of cases, indexed by the object´s attributes. Based on the problem´s description, the indexes point out which attributes should be compared, finding out the case that can be useful for the solution. Each attribute receives a weight according to their degree of importance in the solution of the case. In our model, we built the indexes using an explanation-based technique, where the specialist points out which attributes are relevant for the solution of the problem[17]. Figure 5 shows the indexes for the cases that described the problem described in Figure 4. The indexes for the *description rules* are *area* and *perimeter/area ratio*; the indexes for *evolution cases* are the *object types* and their *spatial relationship*.

After creating and indexing the knowledge base, we can then create the history of all objects. Each object is considered to be a new problem and processed separately in two phases (see Figure 6). Processing starts by taking the objects from the *Geospatial Objects Database* that contains snapshots of the geospatial objects at different moments. For the example shown in Figure 2 (evolution of Brazil´s borders), the database would contain six snapshots for the years 1709, 1789, 1822, 1889, 1943 and 1990. The CBR system starts at the earliest snapshot. For each object in each snapshot, the CBR tries to find out its type based on the *Description Cases Database* that contains a set of cases, defined by a domain expert. The CBR system measures the similarity between each case stored in the database and the new object, according to their attribute values. Expressed as a real number between 0.0 (no similarity) and 1 (equality), similarity is calculated for each case in the database according to the attribute values. The software recovers the best match, shows it to the expert for confirmation, and stores the confirmed solutions in the *Typed Geospatial Objects Database*. After processing all the information from the first snapshot, the software recovers all objects from the next snapshot in the *Geospatial Objects Database.* It describes them according to the rules of the *Description Cases Database* and stores them in the *Typed Geospatial Objects Database.*

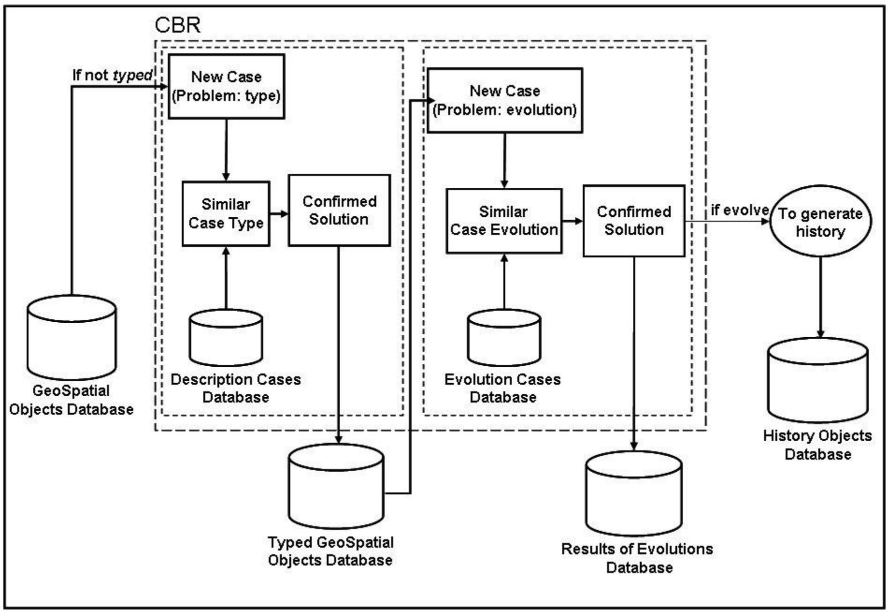


Fig. 6. CBR System Architecture for Geospatial Object History Extraction

The second phase of the CBR-based software takes the objects from two consecutive snapshot of the *Typed Geospatial Objects Database* to describe their evolution. It compares the objects from the two consecutive snapshots according to the rules of the *Evolution Cases Database*. These rules consider the objects' spatial relationships to find out if two objects should be merged or if an object should be split and then joined with another. The software creates the history of each object and stores it in *History Objects Database*. Thus, the method has the following steps, considering the snapshots are stored in increasing temporal order, taking time as a sequence *T={1, ..., n}:*

1. *Let T = 1.*
2. *Take the objects from time T from the Geospatial Objects Database. Describe these objects according to the Description Cases Database. Store the results in the Typed Geospatial Objects Database.*
3. *Take the objects from time T+1 from the Geospatial Objects Database. Describe these objects according to the Description Cases Database. Store the results in the Typed Geospatial Objects Database.*
4. *Compare the objects of times T and T+1 using the Evolution Cases Database. Evolve the objects if possible. Store the results in a History Objects Database.*
5. *If there are further snapshots in the Geospatial Objects Database, make T = T+1 and go to step 2 above. Otherwise, exit the program.*

To better explain the possible uses of the proposed technique, we present a case study using real data in the next section.

5. Land change objects in Brazilian Amazonia: a case study

This section presents a case study about extraction of the history of geospatial objects associated to deforestation areas in the Brazilian Amazonia rainforest. It motivation is the surveying work carried out by the National Institute for Space Research (INPE). Using remote sensing images, INPE provides yearly assessments of the deforestation in Amazonia region that are considered to be precise by the international community. INPE's measures show that close to 250,000 km^2 of forest were cut in Amazonia from 1995 to 2007 [18]. Given the extent of deforestation in Amazonia, it is important to figure out the agents of deforestation. We need to assess the role and the spatial organization of the different agents involved in land change. Our idea is to associate each land change patch, detected in a remote sensing image to one of the agents of change. Extensive fieldwork points out the different agents involved in land use change (small-scale farmers, large plantations, cattle ranchers) can be distinguished by their different spatial patterns of land use [19] [20]. These patterns evolve in time; new small settlements emerge and large farms increase their agricultural area at the expense of the forest. Farmers also buy land from small settlers to increase their property for large-scale agriculture and extensive cattle ranching. Therefore, our CBR technique will aim to distinguish land change objects based on their shapes and spatial arrangements.

For our case study, we selected a government-planned rural settlement called Vale do Anari, located in Rondônia State, Brazilian Amazonia Tropical Forest. This settlement was established by INCRA (Colonization and Land Reform National

Institute) in 1982, with lots size of around 50 ha (see Figure 8). The choice considered two reasons: one of the authors has done extensive fieldwork on the area [21, 22], and this area had already been studied in a previous work [9]. In this previous work, Silva et al [9] used a decision-tree classifier to describe shapes found in land use maps extracted from remote sensing images. They then associated these shape descriptions to the different types of social agents involved in land use change.

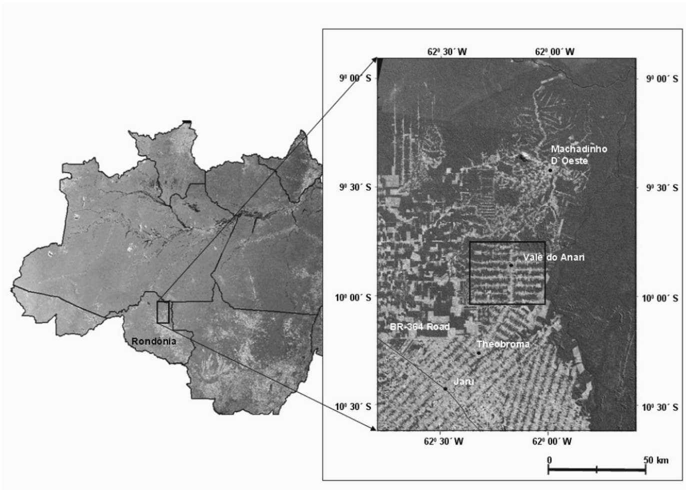


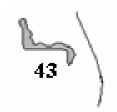
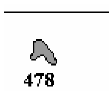
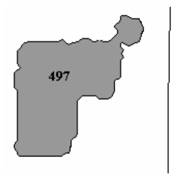
Fig. 8. Location of the study area. The Brazilian Amazonia is on the left, and the Vale do Anari area in the state of Rondônia is on the right. Light-coloured areas point to deforestation.

Silva et al.´s work did not find out how individual objects evolved, but presented his results simply comparing the overall types of objects found in each snapshot. Since his work found good descriptive rules for the different object types, it motivated the authors to use the CBR technique for eliciting the history of the objects in the Vale do Anari region. In our study, we distinguish three types of land change objects: *Small Lot* (LOTS), *Along Road Occupation* (AR) and *Concentration Areas* (CON). The characteristics of those objects are:

- *Small Lot*: Small settlement household colonists living on subsistence agriculture or small cattle ranching. Their spatial patterns show up as *linear* patterns following planned roads built during earlier stages of colonization.
- *Along Road Occupation*: Small household colonists associated to settlement schemes living on subsistence agriculture or small cattle ranching. Their spatial patterns show up as *irregular* clearings near roads, following parcels defined by the planned settlement.
- *Concentration*: Medium to large farmers, associated to cattle ranches larger than 50 ha. This pattern results from selling several 50 ha lots to a farmer aiming to enlarge his property. Their spatial patterns are *regular* ones, close to roads or population nucleus.

To describe these object types, we use both, their geometric attributes and their spatial relations, as shown in Table 2. We define a linear shape as an object with perimeter/area ratio greater than 50. An irregular shape is an object with a perimeter/area ratio smaller than 10 and an area smaller than 50 ha. A regularly shaped object is one with a perimeter/area ratio smaller than 50 and an area greater than 50 ha. The spatial relation used to distinguish this object type is its *adjacency to roads*. This rule considers that early settlers in the region occupied and cleared their lots preferably close to the roads, ensuring accessibility to urban nucleus and services.

Table 2. Description of deforestation objects

Example	Geometry	Spatial relation	Object Type
	Linear shape	Touches the road	*Along road occupation*
	Linear shape	Doesn´t touch the road	*Small lot*
	Irregular shape	Touches the road	*Along road occupation*
	Irregular shape	Doesn't touch the road	*Small lot*
	Geometric shape	Indifferent	*Concentration*

Thus, the *Description Rules* (DR) for deforestation objects are:

DR1. "A geometric spatial pattern is an object of type land concentration".

DR2. "An irregularly shaped pattern that touches a road is an object of type along road occupation".

DR3. "An irregular spatial pattern doesn't touch a road is an object of type small lot".

DR4. "A linear spatial pattern that touches a road is an object of type along road occupation".

DR5. "A linear spatial pattern that doesn't touch a road is an object of type small lot".

A subset of the deforestation objects in the Vale do Anari is shown in Figure 9. The sequence starts with objects representing 1982-1985 deforestation on its right side. The next set of *deforestation objects* represents new deforested areas detected during the 1985-1988 period and so forth. These three year snapshots show how deforestation occurred; the objects' labelling was confirmed by experts on deforestation domain. On the left side of Figure 9 the deforestation objects detected in the intervals of three years are shown and linked to an attribute table by an identification number.

After setting up the definition rules, the next step is defining the evolution rules that will make up the history of the object. These rules depend on the object´s type as well as its adjacency relation with the other objects. An object of type *along road occupation* does not evolve, since it signals the start of the occupation. When objects of type *small lot* touch each other, they are merged creating a new *small lot*. When an object of the *concentration* type touches an object of types *concentration* or *small lot*, they are merged and the result is a new *concentration*. A small lot object type with area greater than 50 ha represents the results of small lots objects that evolved along time. If a concentration object type touches a small lot object with area greater than 50 ha it doesn´t evolve. The evolution rules for typed deforestation objects are:

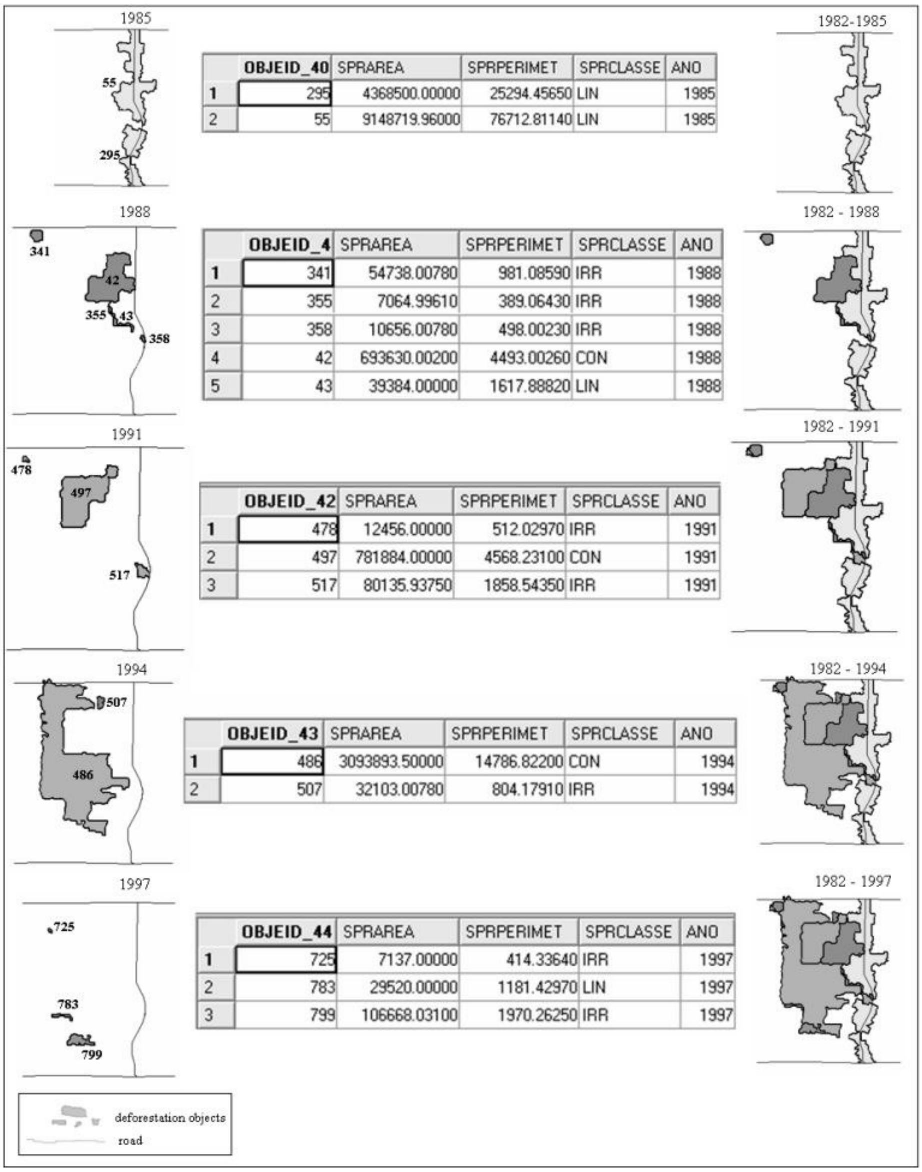
ER1 – "Two adjacent land concentration objects are merged and the new object is a land concentration".

ER2 – "An object of type along road occupation is not merged with other objects".

ER3 – "Two adjacent small lot objects are merged and the new object produced is a small lot".

ER4 – "A small lot with area < 50 ha adjacent to a land concentration object is merged with it and the result is a land concentration object".

ER5 – "A small lot with area >= 50ha and adjacent to a land concentration object is not merged with other object."



	OBJEID_40	SPRAREA	SPRPERIMET	SPRCLASSE	ANO
1	295	4368500.00000	25294.45650	LIN	1985
2	55	9148719.96000	76712.81140	LIN	1985

	OBJEID_4	SPRAREA	SPRPERIMET	SPRCLASSE	ANO
1	341	54738.00780	981.08590	IRR	1988
2	355	7064.99610	389.06430	IRR	1988
3	358	10656.00780	498.00230	IRR	1988
4	42	693630.00200	4493.00260	CON	1988
5	43	39384.00000	1617.88820	LIN	1988

	OBJEID_42	SPRAREA	SPRPERIMET	SPRCLASSE	ANO
1	478	12456.00000	512.02970	IRR	1991
2	497	781884.00000	4568.23100	CON	1991
3	517	80135.93750	1858.54350	IRR	1991

	OBJEID_43	SPRAREA	SPRPERIMET	SPRCLASSE	ANO
1	486	3093893.50000	14786.82200	CON	1994
2	507	32103.00780	804.17910	IRR	1994

	OBJEID_44	SPRAREA	SPRPERIMET	SPRCLASSE	ANO
1	725	7137.00000	414.33640	IRR	1997
2	783	29520.00000	1181.42970	LIN	1997
3	799	106668.03100	1970.26250	IRR	1997

Fig. 9. Sequence of *deforestation objects*

The CBR software builds the *Description Cases Database* using the *description rules* and the *Evolution Cases Database* using the *evolution rules*. After creating these databases, it considers all deforestation objects using the procedure described in Section 4 above. For each new object, it looks for a similar case in *Description Cases Database* to define its type. The next step is to apply the evolution rules. Given an object´s type and spatial arrangements, the CBR software looks for similar cases in the *Evolution Cases Database.* Based on these cases, it finds out the history of each object, which is stored for later retrieval. For each object, the history database keeps track of its evolution, including the originating objects (if the new objects results from a merge operation). The results produced by the CBR for a sample of the *deforestation objects* are presented in Figure 10.

Report Object's History

New Object	Father's Object 1	Type	Year	Father's Object 2	Type	Year	Result	New Area	Year
10	9	Concentration	1997	799	Small Lot	1997	Concentration	4858478,5447	1997
9	8	Concentration	1997	783	Small Lot	1997	Concentration	4751810,5137	1997
8	7	Concentration	1994	725	Small Lot	1997	Concentration	4722290,5137	1997
7	6	Concentration	1994	1	Small Lot	1991	Concentration	4715153,5137	1994
6	5	Concentration	1994	4	Concentration	1994	Concentration	4647959,5059	1994
5	2	Concentration	1991	507	Small Lot	1994	Concentration	1507617,0098	1994
4	3	Concentration	1994	43	Small Lot	1988	Concentration	3140342,4961	1994
3	486	Concentration	1994	355	Small Lot	1988	Concentration	3100958,4961	1994
2	42	Concentration	1988	497	Concentration	1991	Concentration	1475514,002	1991
1	478	Small Lot	1991	341	Small Lot	1988	Small Lot	67194,0078	1991

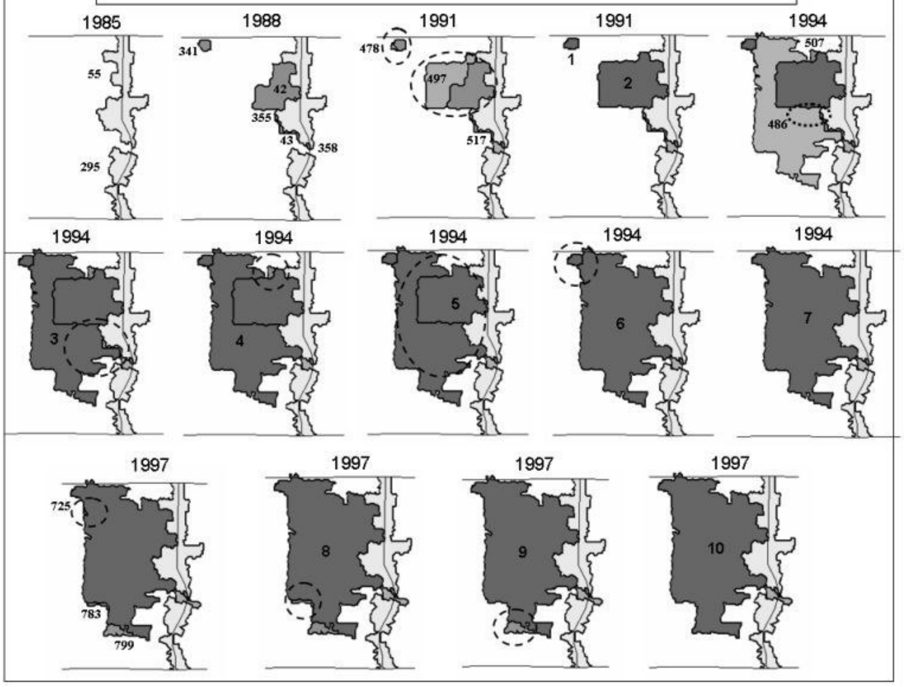


Figure 10. Example of the history of *deforestation objects*.

The report of the object's history shows how deforestation objects evolved. Until 1991, no objects evolved due to rule ER2: "*An object of type along road occupation is not merged with other objects*". In 1991, the object 478 merged with the object 341 following rule ER3 ("*Two adjacent small lot objects are merged and the new object is a small lot"*) and the result is the object 1. Also in 1991, object 497 merges with object 42 according to rule ER4 (*"A small lot with area < 50 ha adjacent to a land concentration object is merged with it and the result is a land concentration object"*), creating object 2. In 1994, land concentration object 486 appears and merges with objects 345 and 43 following rule ER4, creating object 4. In the same year, object 2 merges with object 507 again following rule ER4, creating object 5. In 1994 object 5 merges with object 4 following rule ER1 ("*Two adjacent land concentration objects are merged and the new object is a land concentration"*), creating object 6. Object 6 is again expanded, producing object 7 when merges with object 1. In 1997, object 7 merges with objects 725, creating object 8. Then it merges with object 783, creating object 9, and finally merges with object 799, producing object 10. The CBR software was thus able to show how land concentration occurred in the region, pointing out the government plan for settling many colonists in the area has been largely frustrated [21]. The process of land concentration in the Vale do Anari settlement described by the CBR software matches what was noted in the interviews performed during fieldwork [21].

6. Conclusions

In this paper, we deal with *evolving objects*. We are interested in cases where the simple rules of merging and splitting are not enough to describe their evolution, since such evolution depends on the object´s *types*. We propose a method that uses previous cases as well as knowledge elicited from a specialist as the main sources of knowledge used to solve new problems. A contribution of our research is the definition a case-based reasoning (CBR) method to describe the object´s type and find out how geospatial objects evolve. Experimental results for the Brazilian Amazonia Tropical Forest corroborate the effectiveness of our proposal. The approach of using typed geospatial objects and evolution rules contributes to solve the problem of automatically modelling and describing the history of evolving geospatial objects.

Use of the CBR software for describing object evolution follows form the work of Silva et al. [9] that developed a method for distinguishing patterns of land use change based on their shapes in static timestamps. Their work did not discuss how spatial patterns evolve in time. The current work addresses the problem of tracking changes during an object's lifetime, based on type-specific evolution rules. In our experiments using case-based reasoning (CBR), we were able to obtain the rules for object evolution and to describe how geospatial objects evolve. The CBR technique proved to be a simple and useful approach to set up the rules for land change trajectories.

In our application domain, CBR presented a satisfactory result, since the knowledge base had only a few cases, which were presented to the expert in an organized way. When there are many data types and different cases, the knowledge base should be generated carefully to avoid conflicting and inconsistent interpretations. Additionally, despite advanced techniques for case indexing and retrieval (neural networks, genetic algorithms), a knowledge base with many cases can have a slow and bad performance. In such cases, the CBR software needs to include adaptation and learning techniques, which also detect inconsistencies in the rules. In this case, the rules would be changed according to the expert´s reaction to examples being presented to him. Adaptation and learning are complex and error-prone techniques that, if not done properly, may result in further inconsistencies in the knowledge base. Therefore, many CBR softwares do not provide an adaptation and learning facility. They simply recover the most similar case and make the solution available for the specialist to determine if it solves his matching problem.

Our experience shows that CBR-based techniques are useful and simple to set up for recovering the history of evolving geospatial objects when there are few types and clear-cut rules for object description and evolution. When there are many types and the evolution rules are complex, the CBR software needs to be carefully designed, and should include a learning phase and techniques for detecting inconsistencies and conflicts. In our work, we consider the CBR software we designed in promising enough; so we plan to extend these CBR techniques for improving the study of land cover change evolution in the Brazilian Amazonia region.

Acknowlegments. Gilberto Camara's work is partly funded by CNPq (grants PQ – 300557/19996-5 and 550250/2005-0) and FAPESP (grant 04/11012-0). Olga Bittencourt's work is funded by CAPES.

References

1. Frank, A.: Ontology for Spatio-temporal Databases. In: Koubarakis, M., Sellis, T. (eds.): Spatio-Temporal Databases: The Chorochronos Approach. Springer, Berlin (2003) 9-78
2. Worboys, M.: Event-oriented approaches to geographic phenomena. International Journal of Geographical Information Science 19 (2005) 1-28
3. Grenon, P., Smith, B.: SNAP and SPAN: Towards Dynamic Spatial Ontology. Spatial Cognition & Computation 4 (2003) 69-104
4. Galton, A.: Fields and Objects in Space, Time, and Space-time. Spatial Cognition and Computation 4 (2004) 39-68
5. Goodchild, M.F., Yuan, M., Cova, T.J.: Towards a general theory of geographic representation in GIS. International Journal of Geographical Information Science 21 (2007) 239–260
6. Markosian, N.: Time. In: Zalta, E.N. (ed.): The Stanford Encyclopedia of Philosophy (Winter 2008)
7. Bittencourt, O., Câmara, G., Vinhas, L., Mota, J.S.: Rule-based evolution of typed spatiotemporal objects. In: VIII Brazilian Symposium in Geoinformatics, GeoInfo2007, Campos do Jordão, Brazil (2007)
8. Mota, J.S., Câmara, G., Fonseca, L.M.G., Escada, M.I.S., Bittencourt, O.: Applying case-based reasoning in the evolution of deforestation patterns in the Brazilian Amazonia. . Proceedings of the 2008 ACM Symposium on Applied Computing (Fortaleza, Ceara, Brazil, March 16 - 20, 2008). SAC '08. , ACM, New York, NY (2008) 1683-1687

9. Silva, M.P.S., Câmara, G., Escada, M.I., Souza, R.C.M.: Remote Sensing Image Mining: Detecting Agents of Land Use Change in Tropical Forest Areas. International Journal of Remote Sensing 29 (2008) 4803-4822
10. Hornsby, K., Egenhofer, M.: Identity-Based Change: A Foundation for Spatio-Temporal Knowledge Representation. International Journal of Geographical Information Science 14 (2000) 207-224
11. Medak, D.: Lifestyles. In: Frank, A.U., Raper, J., & Cheylan, J.-P. (ed.): Life and Motion of Socio-Economic Units. ESF Series. Taylor & Francis, London (2001)
12. Cardelli, L., Wegner, P.: On Understanding Type, Data Abstraction, and Polymorphism. ACM Computing Surveys 17 (1985) 471-552
13. Kolodner, J.: Case-based reasoning. Morgan Kaufmann Publishers Inc. San Francisco, CA, USA (1993)
14. Aamodt, A., Plaza, E.: Case-based reasoning: foundational issues, methodological variations and system approaches. AI Communications 7(1) (1994) 39–59
15. Wangenheim, C.G., Wangenheim, A.: Raciocínio Baseado em Casos, Barueri: São Paulo. (2003)
16. Motoda, H., Mizoguchi, R., Boose, J., Gaines, B.: Knowledge Acquisition for Knowledge-Based Systems. IEEE Expert: Intelligent Systems and Their Applications 6 (1991) 53-64
17. Lorenzi, F., Abel, M.: Aplicando raciocínio baseado em casos na investigação de irregularidades nas internações hospitalares (Applying CBR for investigating problems in hospitals). Brazilian Computer Congress, Itajaí, SC. (2002) 13
18. INPE: Monitoramento da Floresta Amazônica Brasileira por Satélite (Monitoring the Brazilian Amazon Forest by Satellite). National Institute for Space Research, Sao José dos Campos (2008)
19. Lambin, E.F., Geist, H.J., Lepers, E.: Dynamics of land-use and land-cover change in Tropical Regions. Annual Review of Environment and Resources 28 (2003) 205-241
20. Silva, M.P.S., Câmara, G., Escada, M.I.S., Souza, R.C.M.: Remote Sensing Image Mining: Detecting Agents of Land Use Change in Tropical Forest Areas. International Journal of Remote Sensing 29 (2008) 4803-4822.
21. Escada, M.I.: Evolução de Padrões da Terra na Região Centro-Norte de Rondônia (Evolution of Land Use Patterns in the Center-North Region of Rondônia). PhD Thesis in Remote Sensing. Instituto Nacional de Pesquisas Espaciais, São José dos Campos (2003) 164 p.
22. Soler, L., Escada, M., Verburg, P.: Quantifying deforestation and secondary forest determinants for different spatial extents in an Amazonian colonization frontier (Rondonia). Applied Geography 29 (2009) 182-193