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ELICITING THE EVOLUTION OF SPATIOTEMPORAL OBJECTS WITH CASE-BASED REASONING

Joice Seleme Mota

Doctorate Thesis at Post Graduation Course in Applied Computing Science, advised by Dr. Gilberto Câmara and Dra. Leila M. G. Fonseca, approved in Month XX, 200X.

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FOLHA DE APROVAÇÃO

"O povo pobre, atraído para lá, foi traído lá mesmo. Tem que ser conduzido de volta a realidade, a lugares onde possam trabalhar de verdade como gente digna e não como formigas daninhas perdidas na floresta".

Saulo Ramos

Ao Casemiro.

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ABSTRACT

One of the main challenges in the information extraction provided by remote sensing images is to model and to represent geographical objects that have their properties changed along the time. This thesis proposes a novel approach based on Case Based Reasoning (CBR) for describing how geospatial objects identified in remote sensing imagery evolve. Given a set of multi-temporal images, the CBR techniques and the expert knowledge in a certain application domain, the approach describes the trajectories of evolution objects. Therefore, it is possible to describe how the objects evolve by retrieving their complete evolving history. The proposed method is tested for two case studies, in the Brazilian Amazonia Forest, for describing the evolution of deforestation patterns, which can enable a better understanding of land use changes in these regions.

EXTRAÇÃO DA EVOLUÇÃO DE OBJETOS ESPAÇO-TEMPORAIS COM RACIOCÍNIO BASEADO EM CASOS

RESUMO

Um dos principais desafios no processo de extração de informação em imagens de sensoriamento remoto é como representar e modelar os objetos geográficos que tem suas propriedades alteradas ao longo do tempo. Esta tese propõe um novo modelo, baseado na técnica de Raciocínio Baseado em Casos (RBC), para descrever a evolução de objetos geoespaciais em imagens de sensoriamento remoto. A partir de uma série de imagens de sensoriamento remoto, onde cada imagem contém o estado dos objetos em um determinado momento, da técnica RBC e do conhecimento do especialista no domínio de uma dada aplicação, o método permite descrever as trajetórias dos objetos em evolução. Dessa forma, é possível descrever como os objetos evoluem, recuperando, assim, a história completa de sua evolução. O método proposto é testado em duas regiões da Floresta Amazônica Brasileira, para descrever a evolução de padrões de desmatamento, que pode ajudar no melhor entendimento dos processos de mudanças no uso da terra nestas regiões.

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1 INTRODUCTION

Modeling and representation of geographical phenomena is a major research area in GIScience. One recent interest in this area is to handle the richness of information present in temporal data and images. Capturing, acting and using landscape dynamics information present on these images is important to understand and to represent the landscape evolution. One alternative for improving the approximation of analysis results to reality is to apply remote sensing knowledge.

One challenge in the knowledge provided by remote sensing images is to model and to represent geographical objects that have their properties changed along the time. We refer to these objects as *spatiotemporal objects* and we distinguish two broad categories. The first category concerns objects whose position and extent change continuously, referred to as *moving objects*. For example, a car can be modeled as a punctual object whose location varies with the time. The second type concerns objects that are bound to specific locations, but whose geometry, topology and properties change in time. We refer to them as *evolving objects*, as for example, which arise in urban cadastre and in land cover change.

Each type of spatiotemporal object needs appropriate data modeling, representation and algorithms. In this context some research areas have been highlighted in an attempt to represent spatiotemporal knowledge such as patterns of mobility and tracking of objects ((MOUZA; RIGAUX, 2004; WEGHE et al., 2005), representation of moving objects (TOSSEBRO; GUTING, 2001; LEMA et al., 2003; GÜTING et al., 2003; GÜTING et al., 2004), strategies for indexing spatiotemporal objects (PFOSER et al., 2000; KWON et al., 2005) and strategies for modeling objects that changes (EGENHOFER; AL-TAHA, 1992; HORNSBY; EGENHOFER, 1997; HORNSBY; EGENHOFER, 1998; CLIFFORD; CROKER. 1998; MEDAK, 1999; HORNSBY; EGENHOFER, 2000: EGENHOFER; AL-TAHA, 1992; CHEYLAN, 2001). Related to evolving objects, we cite (HORNSBY; EGENHOFER, 2000; MEDAK, 2001) that propose tracking

the changes that occur during an object's lifetime, such as creation, splitting and merging. In spite of all this research, eliciting the evolution of spatiotemporal objects continues to be an important challenge in spatiotemporal modeling and this is the subject of this thesis.

1.1 Problem definition

In this thesis, we deal with *evolving objects*. We use the concept of *spatiotemporal evolution* to indicate transformations that happen to objects along time. We are interested in situations where simple rules of merging and splitting are not enough to describe the object's evolution. In these situations, the objects are defined not only by their shape and properties but also by their meaning and constraints that determine their evolution. Consider the changes that can occur in a city. Firstly, consider the example that two cities join. Independently of the reason, for example a conquest or a settlement, we can infer that the result will be a new city, by merging the two early ones. In another situation, consider the case of joining a city and a state. The result of this operation is not simple because, probably, one of the objects will change type and properties according to the specific type of the other object.

What one can observe is that when we are dealing with evolution, expansions and contractions it is common that junctions and splitting are type-dependent. In this example and similar it is important to know the entire evolution of each object and to store its change history, keeping track of meaning-dependent cases. This requires a higher-level of semantics beyond the basic operations such as creation, splitting and merging to model the evolution of objects. Therefore, to be able to record the complete history of each object, we need a model that uses previous evolution examples and expert knowledge as the main knowledge sources to solve this modeling evolution problem. In this context we define the specific research query of this thesis as "*How to elicit the evolution of spatiotemporal objects?*"

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Considering that there are different categories of spatiotemporal objects that evolve and depend on their types and evolution constraints, this thesis was oriented by the following hypotheses:

- a) it is possible to elicit information from some source of knowledge to define spatiotemporal object types.
- b) spatiotemporal objects have constraints that govern their evolution.
- c) it is possible to apply Case-Based Reasoning as a strategy to identify, store and recover the history of evolving objects.

1.2 Motivation

The motivation to developing an approach to handle the evolution of objects was based on the need to solve the challenge of deal with the evolution process in the landscape.

A way to detect the land use and land cover change in the biodiversity, provoked by human actions, is the use of remote sensing techniques. Remote sensing is a useful technology to survey tropical forest. Images can be acquired everyday by a constellation of satellites (FREITAS; SHIMABUKURO, 2007). Mapping and surveying their deforestation (including selective cutting) allows the analysis of patterns and causes of the tropical forest loss (ARMENTERAS *et al.*, 2006; FERRAZ *et al.*, 2005; LAURANCE *et al.*, 2002; MENDOZA; ETTER, 2002; PERZ *et al.*, 2005; PFAFF; SANCHEZ-AZOFEIFA, 2004; WALKER, 2004). The forest monitoring and the land use and land cover changes needs to be analyzed in different times using satellite images or aerial pictures (LAMBIN et al., 2003).

In Brazilian Amazonia, the main processes of land cover change are linked to agricultural producers and cattle ranchers that use different land use strategies (BECKER, 1997). The type of occupation in areas of expansion of the agricultural frontier is associated to different processes of land cover change.

Escada (2003) defines a land use typology that represents the main processes associated to different categories of rural producers fixed in the region and to different occupation processes. Different agents involved in the land use change (small farmers, farmers, cattle breeders) can be distinguished by their different land use patterns. These patterns evolve in time; new small areas emerge and large farms increase their agricultural area at the expense of the forest (SILVA et al., 2008).

Silva et al. (2008) proposed a method to detect the agents of land change in the Amazonia forest. They associate each land change pattern to one of the agents of change. They use a decision-tree classifier to describe shapes found in deforestation maps and then associate these shape descriptions to the different types of social agents involved in land use change. In their approach, each pattern represents a new object in its corresponding time and, therefore, it characterized as a new pattern. Patterns found in one map can be linked to others detected in earlier maps, thus enabling a description of the trajectory of their changes. This description allows us to understand the land use changes that are detectable in remote sensing imagery.

1.3 Objectives and Contributions

The objective of this thesis is to develop an approach to elicit the evolution of spatiotemporal objects. The evolution process is analyzed to understand the conditions that define how and when the properties of an object change. The approach uses a Case-Based Reasoning technique that provides mechanisms to define the meaning of evolution and constraints, and to extract rules of changes. Therefore, our approach allows storing and retrieving the evolution of objects. It takes into account that:

 a) spatiotemporal objects are treated as evolving objects that have types and evolution constraints;

- b) previous evolution examples and expert knowledge in the specific application domain should be used to model the pattern evolution;
- c) CBR techniques are adequate for eliciting the evolution a spatiotemporal object.

The main contributions of the method proposed in this thesis are

- a) development of an approach to extract change rules in spatiotemporal objects depending of the application domain.
- b) storage and representation of the history of spatiotemporal objects.
- c) enabling the understanding of future evolutions based on the comparison with existing historical data.

To validate our method, two case studies are presented aiming to extract the evolution of deforestation patterns in Amazonia region. The main objective is to identify land concentrations in deforested areas inside settlement projects in Rondônia state. Using the CBR technique, a set of multi-temporal images, and expert knowledge, it was possible to store and recover the evolution history of deforestation objects.

1.4 Thesis Layout

This thesis is structured in four chapters. The second chapter presents the developed approach for eliciting the spatiotemporal objects evolution, the architecture of CBR and a simple case study to corroborate the approach. The application of our approach is presented in the third chapter through two complete case studies. We extracted land use patterns evolution in regions of the Brazilian Amazonia. The objects were identified in *ale do Anari* and *Machadinho D'Oeste* INCRA's settlement projects, in Rondônia state, Brazil. The fourth chapter presents the conclusions.

2 CASE-BASED REASONING FOR ELICITING THE EVOLUTION OF GEOSPATIAL OBJECTS¹

2.1 Introduction

The computational modeling of geospatial information continues to be, after decades of research, a 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 modeling and representation of geospatial objects whose properties change (FRANK, 2003; GALTON, 2004; GOODCHILD *et al.*, 2007; GRENON; SMITH, 2003; WORBOYS, 2005). 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 (Geographical Information System) is not only an issue of handling time-varying data. It also concerns how objects gain or lose their identity, how their properties change, which changes happen simultaneously, and what causes change. As Goodchild et al. (2007) point out, the distinction between geospatial entities as continuous fields or discrete objects also applies in the temporal domain. In this chapter, we deal with computational models for time-varying discrete geospatial entities.

This chapter 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*

¹ Based on: MOTA, J.; CAMARA, G.; ESCADA, M. I.; BITTENCOURT, O.; FONSECA, L.;VINHAS,L., 2009, Case-Based Reasoning for Eliciting the Evolution of Geospatial Objects. **Conference on Spatial Information Theory: COSIT'09.** (accepted)

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 examples as well as knowledge obtained from an expert as the main sources of knowledge used to solve new problems.

In this context, we propose a computational method that contains a set of rules that describe how *geospatial objects* evolve, based on a sample of existing situations. For this task we have used the Case-Based Reasoning (CBR) technique, which defines a set of rules that arise from knowledge about the application domain.

In what follows, we review previous work (section 2.2) and review CBR (section 2.3). In section 2.4, we describe our proposal. In section 2.5 we describe an experiment where we applied our method to a spatiotemporal study of deforestation evolution. This chapter builds on previous work by the authors (BITTENCOURT *et al.*, 2007; MOTA *et al.*, 2008; SILVA *et al.*, 2008)

2.2 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 from others during all its life. Life is the time period from the object's creation until its elimination. Genealogy implies managing the changes that occur to an object has during its life. Hornsby and Egenhofer (2000) stress the need to preserve an object's identity when its geometry, topology, or attributes change, a view supported by Grenon and

Smith (2003). Consider parcels in an urban cadastre. A parcel can have its owner changed, 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 (HORNSBY; EGENHOFER, 2000; MEDAK, 2001). However, these authors do not consider the problem of extracting evolution rules from the objects themselves. They consider objects of a single type. In this thesis, we consider objects of different types and we provide ways to extract their evolution rules.



Figure 2.1 – Example of object evolution.

To take a simple motivational example, consider Figure 2.1, 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 2.2. Each polygon in Figure 2.2 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 and exchange of external areas (through international treaties). Suppose we want to devise a procedure that, given the snapshots shown in Figure 2.2, tries to extract the history of Brazil's internal and external borders. Such 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.



Figure 2.2 – Evolution of internal and external borders of Brazil from 1709 to 1990. Source: http://wikipedia.pt.org

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 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 (CARDELLI; WEGNER, 1985). 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, for objects of type '*Country*' and those of type '*State*' we need different rules to describe their evolution. Models

in which objects have different types and evolution rules are richer and more powerful than typeless ones.

2.3 Case Based Reasoning

Case-Based Reasoning (CBR) is a problem-solving technique that recalls and adapts solutions previously used in similar problems (AAMODT; PLAZA, 1994; KOLODNER; JONA, 1991; WANGENHEIM; WANGENHEIM, 2003). CBR is based on human natural reasoning and there is evidence that people use CBR in their daily reasoning. The description of existent problems, known as *cases*, suggests a way of solving a new problem and to interpret the current situation (LORENZI; ABEL, 2002). The basic cycle of processing CBR is composed by four main tasks: 1) recover the most similar cases in a case database, 2) reuse the cases to solve the problem, 3) revise the proposed solution and 4) store the experience representing the current case for future reuse (AAMODT; PLAZA, 1994).

CBR can be applied to the most varied domains. In that diversity, we can distinguish two basic types of CBR implementation: totally automatic systems and recovery systems based on cases (KOLODNER; JONA, 1991). Automatic systems solve the problem in an autonomous way and include interaction mechanisms to evaluate the results of their decisions. Information recovery systems based on cases, use people to solve the problems, as an extension of the memory of the specialist who must use reasoning and make the decision (KASTER *et al.*, 2001). Our CBR is based on this second implementation type.

Case-based reasoning presents characteristics that motivate its application in environmental modeling. Environmental problems are inherently complex and in general insufficiently known and modeled. CBR is a technique in which knowledge is modeled by samples, so it is not necessary to model in a formal way the knowledge domain (KASTER *et al.*, 2001). The application developed in Kaster (2001) has a mechanism of intelligent recovery, and the edition of

models uses techniques of Case-Based Reasoning. Its goal is to aid users to develop new problem-solving strategies for environmental planning. It starts from strategies already stored in a base on scientific workflows that interact with a Geographic Information System (GIS). Another application that combines CBR and GIS is the system of classification of soils named ZONATION (HOLT; BENWELL, 1999). This system allows specialists to do classifications based in previous instances, using specific knowledge of the domain.

Other CBR approaches supporting applications related to environmental decisions have been developed. For example, warning system on infestations and grasshoppers combining CBR and reasoning based on models (HASTINGS, 1996). In Verdenius (1999) a system applied CBR for the domain of waters and sewer treatment using plants and microorganisms. The system consists in managing the level of oxygen and deciding in several situations which measure must be taken.

2.4 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. Following (AAMODT; PLAZA, 1994), 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 spatiotemporal objects evolve (shown in Figure 2.3) 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.



Figure 2.3 – General view of CBR method for eliciting geospatial objects evolution.

The domain expert defines two types of rules to characterize the objects' evolution: *description rules* and *evolution rules*. The *description rules* define the types of geospatial objects. The *evolution 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 relationship, including topological predicates such as 'cross', 'close to' and 'touch'. Consider Figure 2.4, where some prototypical land change objects are portrayed. Figure 2.4(a) shows three objects at time T1. At time T2, three new objects appear as shown in Figure 2.4(b). After application of the description and evolution rules described below, the resulting objects are shown in Figure 2.4(c).

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

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

DR3. An object with perimeter/area ratio greater than 10 hectares and whose area is more than 50 hectares is a Large Geometric object.

These rules allow us to identify the objects in Figure 2.4, as shown in the labels assigned to each object. For this example, 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.



Figure 2.4 – 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 *SmallGeometric* objects shown in Figure 2.4(b) are merged with the adjacent *LargeGeometric* objects, thus resulting in a spatial expansion of the latter. This example shows the need for a system that is able to represent the *description* and *evolution rules* and apply them to extract the history of a set of objects. This system architecture is described in the next section.

2.5 CBR-based Geospatial Object History Extractor

This section describes the architecture of a geospatial history extractor based on CBR (Case-Based Reasoning) technique. A CBR system stores knowledge as a set of cases. Each case contains data about a specific episode, with its description and the context in which it can be used (WANGENHEIM; WANGENHEIM, 2003). 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 (MOTODA *et al.*, 1991), 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:

1. describing the objects in their environment (description rules).

2. analyzing this outcome of spatial operations between the objects (*evolution rules*).

After the expert produces the rules, the CBR system stores a set of rules for each case, as shown in Figure 2.5.



Figure 2.5 – 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 (among 0 and 1) 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 (LORENZI; ABEL, 2002). Figure 2.5 shows the indexes for the cases that describe the problem presented in Figure 2.4. The indexes for the *description rules* are area and perimeter/area ratio; the indexes for *evolution cases* are the *objects 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 as a new problem and processed separately in two phases. Processing starts by taking the objects from snapshots of the geospatial objects at different periods of time. For the example shown in Figure 2.2 (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 Rules, 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. After processing all the information from the first snapshot, the system recovers all objects from the next snapshot. It describes them according to Description Rules and stores them.

The second phase of the CBR-based system takes the typed objects from two consecutive snapshots to describe their evolution. The specialist verifies if the

objects are neighbors and the system compares the objects from the two consecutive snapshots according to the rules of the *Evolution Rules*. These rules consider the objects' spatial relationships to find out if two objects should be merged in agreement with their description. The system creates the history of each object and stores it in the *History Objects Database*. The attributes of the *History Objects Database* are:

1. New Object: the new identification for the object created.

- 2. *FatherObject1*: identification of the first object that generated the new.
- 3. YearObject1: year of the first object that generated the new.
- 4. *FatherObject2*: identification of the second object that generated the new.
- 5. YearObject2: year of the second object that generated the new.
- 6. *Result*: the new description for the new object.
- 7. Year result: the year in which the new object was created.
- 8. *New area:* the area of the new object given by the sum of the areas of the objects that were merged.

These attributes keep the origin of the new object allowing the recovery of its history. Considering that the snapshots are stored in increasing temporal order, taking time as a sequence $T = \{1, ..., n\}$ the evolving process can be described in the following steps:

- 1. Let T = 1.
- Take the geospatial objects from time T. Describe these objects according to the Description Rules. Store the results in Typed Geospatial Database.

- 3. Take the geospatial objects from time T+1. Describe these objects according to the Description Rules. Store the results in the Typed Geospatial Database.
- Compare the typed geospatial objects of times T and T+1 using the Evolution Rules. Evolve the objects if possible. Store the results in a History Objects Database.
- 5. If there are further snapshots, 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.

2.6 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. The 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 data show that around 250,000 km² of forest were cut in Amazonia from 1995 to 2007 (INPE, 2005). In spite of the importance of this subject, there are rare examples of planning and monitoring of rural settlements project in the Brazilian Amazonia that use the potential of Geoinformation techniques to understand and to integrate analytically the trajectories of landscape in transformation (BATISTELLA; BRONDIZIO, 2004).

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) that can be distinguished by their different spatial patterns of land use (LAMBIN *et al.*, 2003) (SILVA *et al.*, 2008). These patterns evolve in time; new small rural 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, CBR 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 of approximately 50 ha (see Figure 2.6). This choice was based on two aspects: the existence of data fieldwork on the area (ESCADA, 2003; SOUZA, 2008 *et al.*), and this area had already been studied in a previous work (SILVA *et al.*, 2008). In this work, Silva et al (2008) used a decision-tree classifier to describe shapes found in land use maps extracted from remote sensing images. They associated these shape descriptions to different types of social agents involved in land use change.

Silva et al., (2008) work did not find out how individual objects evolved, but presented their results comparing the overall types of objects found in each snapshot. They classified deforestation patterns as: Linear (LIN), Irregular (IRR) and Geometric (GEO) in the *Vale do Anari* region (SILVA *et al.*, 2008). These objects associated a deforestation patterns were the input of our system. 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:

 Along Road Occupation: 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.

- Small Lot: 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 the selling of several 50 ha lots to a farmer aiming to enlarge his property. Their spatial patterns are *geometric* ones, close to roads or population nuclei.



Figure 2.6 – 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.

The types of some land change objects are presents in Table 2.1.

Example	Geometry	Spatial relation	Object Type	
295	Linear shape	Touches the road	Along road occupation	
43	Linear shape	Doesn't touch the road	Small lot	
517	Irregular shape	Touches the road	Along road occupation	
478	Irregular shape	Doesn't touch the road	Small lot	
497	Geometric shape	Indifferent	Concentration	

Table 2.1 - Description of deforestation objects: some examples.

Thus, the *Description Rules* (DR) for deforestation objects in our case study 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 2.7. The sequence starts with objects representing 1982-1985 deforestation on the right side. The next set of *deforestation objects* represents new deforested areas detected during the 1982-1985 period and so forth. These three year snapshots show how deforestation occurred; the objects' labeling was confirmed by experts on deforestation domain. On the left side of Figure 2.7 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 to define the evolution rules that will make up the history of the object. These rules depend on the object's type as well as on 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 generating a new *small lot*. When an object of the *concentration* type touches an object of *concentration* or *small lot* types, they are merged and the result is a new *concentration*. A small lot object type with area greater than 50 ha represents the result of merging small lots objects 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".

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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."



Figure 2.7 – Sequence of *deforestation objects*.

The CBR system builds the *Description Rules Database* and the *Evolution Rules Database*. After creating these databases, it considers all deforestation objects using the procedure described in Section 2.4. For each new object, it looks for a similar case in *Description Rules Database* to define its type. The next step is to apply the evolution rules. Given an object's type and spatial

arrangements, the CBR system looks for similar cases in the *Evolution Rules 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 2.8.

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 ER1, ("Two adjacent land concentration objects are merged and the new object is a land concentration"), creating object 2. In 1994, land concentration object 486 appears and merges with object 43 following 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 3. In the same year, object 2 merges with object 517 again, following rule ER4, creating object 4. In 1994 object 3 merges with object 355, following rule ER4, creating object 5. Still in 1994, object 4 merges with object 5, following rule ER1, creating object 1, that is again expanded, producing object 7, which 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 system was thus able to show how land concentration occurred in the region, showing that the government plan for settling many colonists in the area has been largely frustrated (Escada, 2003). The process of land concentration in the Vale do Anari settlement described by the CBR system matches what was noted in the interviews performed during fieldwork (Escada, 2003).



Figure 2.8 – Example of the history of *deforestation objects*. (Continues)



Figure 2.8 – Conclusion.

In this chapter, we dealt 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. The approach of using typed geospatial objects and evolution rules contributes to solve the problem of automatically modeling and describing the history of evolving geospatial objects.

3 DETECTING THE EVOLUTION OF DEFORESTATION OBJECTS IN AMAZONIA USING CASE-BASED REASONING

3.1 Introduction

This chapter presents a case study about evolution of deforestation objects in the Brazilian Amazonia rain forest. The Brazilian National Institute for Space Research (INPE, 2005)) uses satellite images to provide yearly assessments of the deforestation in Amazonia region. According to INPE's estimation, close to 700,000 km² of forest were cut in Amazonia in the period from 1988 to 2000 (CÂMARA *et al.*, 2006). Land cover change in Amazonia has multiple causes and local agents, including rubber-tappers, cattle ranchers, large agricultural farmers, small-scale landowners, and government-induced settlements (ALVES *et al.*, 2003). Given the large extent of the Amazonia and the need of polices to reduce deforestation and to promote regional planning and sustainable development it is important to figure out the main processes and agents associated to deforestation. The deforestation pattern analysis using CBR and the structural classifier allow us to establish this connection.

This chapter is an extended and fully revised version of earlier work by Mota et al., (2008).

3.2 Domain application

Our case study concerns government-planned rural settlements in *Vale do Anari* and *Machadinho D'Oeste* municipalities, located in the state of Rondônia. Figure 3.1 presents the location of *Vale do Anari and Machadinho D'Oeste* study areas. Both settlements were established in 1982 by INCRA (National Institute of Colonization and Land Reform) in the northeast of Rondônia State with initial areas of 1246 km² and 2129 km², respectively, when several families received a 50 ha land parcel (SOLER *et al.*, 2009). They present similar biophysical characteristics and lot sizes, but with significant differences in their spatial configurations and planning (BATISTELLA, 2001).

According to (BATISTELLA *et al.*, 2003; ESCADA, 2003) during the 1990's, a land concentration process started to occur. Capitalized farmers started to accumulate land parcels from the original settlers creating large farms for cattle-raising (ESCADA *et al.*, 2005).



Figure 3.1 – Geographic Location of Vale do Anari and Machadinho D'Oeste in Rondônia state, Brazil.

The focus of these case studies is on the history of deforestation evolution as a proxy of the process of land concentration. This process, when occurs in agrarian settlements created by INCRA is not licit and can be described as the successive acquisition and accumulation of land lots by few and capitalized farmers (ESCADA, 2003).

To detect deforestation pattern dynamics and to associate them to different agents and processes, three spatial patterns were recognized in the analysis of deforestation data in *Vale do Anari* such as: irregular, linear and geometric (SILVA *et al.*, 2008). The typology and the semantic associated to these deforestation patterns are described as follow:

Linear. Deforestation objects distributed along roads, associated to family household and small farms. This pattern occurs mostly in the beginning of the establishment of the settlement project, following the roads which provide easier accessibility to urban services. The main land use is subsistence agriculture, coffee plantation and/or cattle breeding for small settlers.

Irregular. Small and irregular deforestation objects close to the roads but not along roads. Deforestation size is less than 50 ha. The main land use is agriculture for subsistence, coffee plantation and/or cattle ranching for small settlers.

Geometric: Large deforestation objects greater than 50 ha. The main land use is cattle ranching. This pattern is associated to medium and big farmers.

In Vale do Anari, agrarian colonization projects are characterized by the well known fishbone patterns, while *Machadinho's* agrarian colonization projects were better planned taking local biophysical conditions into account leading to dendritical deforestation patterns (SOLER *et al.*, 2009). A difference can be explained by the different ways of planning. *Vale do Anari* settlement was planned without taking the local topography into account and *Machadinho D'Oeste* was planned with roads and parcels following the watershed topography. Although different, both patterns followed the design of the roads and the proportional amount of deforestation between them has been quite similar along the years of colonization (INPE, 2007). However, the dendritic patterns in *Machadinho D'Oeste* appear to result in less fragmented forest, which is reinforced by several conservation reserves spread among the agrarian projects of this municipality (SOLER *et al.*, 2009). Therefore, *Machadinho D'Oeste* presents a new deforestation pattern in relation to *Vale do Anari*, described as follows:

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Large_Irregular: Large deforestation objects greater than 90 ha. The main land use is cattle ranching. This pattern is associated to medium and large farmers.

Those patterns were classified in *Vale do Anari* and *Machadinho D'Oeste* (SILVA et al, 2008) for the period of 1985 to 2000. In this classification, a land concentration pattern was detected that differs from the typical pattern of settlement projects, associated to linear and small irregular deforestation objects. The typology and the semantics associated to these deforestation patterns are illustrated in Figure 3.2



Figure 3.2 – Deforestation Patterns of Vale do Anari and Machadinho D'Oeste. (Continues)



Figure 3.2 – Conclusion.

In this thesis we consider deforestation patterns as *deforestation objects*. To describe the evolution of these objects we propose the use of CBR technique allowing to identify land concentration patterns and to track their history defining how the patterns of land concentration are formed. To understand the history of deforestation, we need to respond to questions such as: *"How do land cover change objects evolve? What happens when two land cover change objects merge? When did land concentration emerge?"*

3.3 Approach and concepts applied

In this section, we present the steps used to build the CBR for representing the history of deforestation objects in Brazilian Amazonia. First of all, the knowledge domain is elicited by the expert domain to model the cases database that contains previous cases solved by him, stored in a relational database. After the cases database generated the reasoning process is implemented. This process

searches in the database for the cases that are the most similar to the problem case. This search is implemented using global similarity techniques (WANGENHEIM; WANGENHEIM, 2003). The results of this reasoning process are used by the evolution process that generates, stores and recovers the history of the deforestation objects. Figure 3.3 shows this CBR structure.



Figure 3.3 – Structure of CBR.

The objects classified by the structural classifier (*deforestation objects database*) are the input of our CBR system. Attributes such as area, pattern and date are automatically used to create the new cases and the context is chosen by specialist. For each new case created, the reasoning process verifies if the deforestation objects evolve or not. If the deforestation objects evolve the history is generated. These steps are detailed in the next sections.

3.3.1 Knowledge acquisition and modeling

In our approach we generated a set of evolution cases from the knowledge domain. We classify them as *description* and *evolution rules*, depending on their function on the evolution process. The set of evolution rules drives the evolution of each deforestation object. The *description rules* define the typed deforestation objects in the database. The type of objects depends on their descriptive, spatial and temporal characteristics, and its spatial relationship in the context.

In this work, the classification of the patterns generated by Silva (2008) is one of the most important attributes for the description of the cases that defines the type of the deforestation objects. However it is not enough, because each object has a different history that takes into account different context, descriptive and spatial characteristics.

Descriptive attributes were added to define deforestation object types. Descriptive attributes are represented by area (the size of the deforestation objects in hectares) and context (whether the deforestation object is close to a road).

Linear or irregular deforestation objects that *touch* the road are classified with the *along the road* type. Linear and irregular deforestation objects that don't have spatial relationships with the road are classified as *small lot*. Geometric and large_irregular deforestation objects with area larger than 50ha and 90ha respectively, are a *land concentration*. The description rules used to indicate these types are present in Table 3.1.

The *evolution rules* determine when two spatiotemporal objects will evolve. The evolution depends on the type of spatiotemporal objects, the temporal information and the spatial relationship with other objects. The spatial relationship used in the analysis to produce the evolution cases is "*touch*". The definition of *evolution rules* is necessary because, in a sequence of images that contains a set of typed spatiotemporal objects, some of them that have spatial relationships with a defined object evolve to a single object and others do not. For the evolving objects, the *evolution rules* generate a new type of object.

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Description Rules	Using in Vale do Anari	Using in Machadinho D'Oeste
DR1. "A geometric spatial pattern with area >= 50ha is a land concentration object".	Yes	Yes
DR2. "A geometric spatial pattern with area < 50ha that touches a road is a along the road object	Yes	Yes
DR3 "A geometric spatial pattern with area < 50ha that doesn't touch a road is a small lot".	Yes	Yes
DR4. "A large_irregular spatial pattern with area >= 90ha is a land concentration object".	No	Yes
DR5. "A large_irregular spatial pattern with area < 90ha that touches a road is a along the road object	No	Yes
DR6 "A large irregular spatial pattern with area < 90ha that doesn't touch a road is a small lot".	No	Yes
DR7. "An irregular spatial pattern with area <50ha that touches a road is a along the road object".	Yes	Yes
DR8. "An irregular spatial pattern with area >=50ha that touches a road is a along the road object".	Yes	Yes
DR9. "An irregular spatial pattern with area <50ha that doesn't touch a road is a small lot object".	Yes	Yes
DR10. "An irregular spatial pattern with area >=50ha that doesn't touch a road is a small lot object".	Yes	Yes
DR11. "A linear spatial pattern with area <50ha that touches a road is a along the road object".	Yes	Yes
DR12. "A linear spatial pattern with area >=50ha that touches a road is a along the road object".	Yes	Yes
DR13. "A linear spatial pattern with area < 50ha that doesn't touch a road is a small lot object".	Yes	Yes
DR14. "A linear spatial pattern with area >= 50ha that doesn't touch a road is a small lot object".	Yes	Yes

Table 3.1 – Description rules for studies areas.

The attributes that define the *evolution rules,* in these case studies are the deforestation objects types and occupation area. The evolution rules are:

ER1. "Two land concentration objects can be merged and the new object is a land concentration".

ER2. "Two small lots < 50 ha can be merged and the new object is a small lot".

ER3. "A along the road object cannot be merged with other object".

ER4. "Two small lots >= 50 ha cannot be merged".

ER5. "A small lot < 50 ha can be merged with a land concentration object and the new object generated is a land concentration".

In these domains application a small lot smaller than 50 ha can indicate several small lots together, not characterizing land concentrations. Therefore a small lot, larger than 50 ha does not evolve.

The Figure 3.4 presents the representation of the rules and the cases database generated.



Figure 3.4 – Cases database.

3.3.2 Reasoning Process

The efficiency of a CBR system is related to its ability to recover the most relevant cases according to the base of cases (LORENZI; ABEL, 2002). It starts from the problem description whose characteristics should be compared, deciding the case that can be useful to reach a solution. To define the attributes that will be used to recovery a case, the explanation-based method was applied. In this method the specialist points out what characteristics are used to identify the solution. In our study cases, the relevant attributes used to compare and to define the type of the objects are: pattern, area and context. On the other hand, for the evolution cases all attributes are used.

The process of recovering cases begins with a problem description and finishes when a better case is found. To judge which case stored in the database is similar or equal to the new problem, is necessary to measure the similarity among them.

The technique used to recovery the cases, was the search for global similarity because the base have few cases. For each case in the base, a similarity value is calculated with the using a similarity measure. This similarity value indicates the degree of similarity between the current problem and the specific case of the cases database. The similarity value is expressed by real number among 0.0 (any similarity) and 1.0 (equality) and it is calculated for each case in the base according to the values of the attributes.

When a new case is created, CBR looks for the most similar case (WANGENHEIM; WANGENHEIM, 2003) in the *description cases database* to define the type of object. After the solution is confirmed by the specialist, the objects with that type are stored in a *typed deforestation objects database*. The next step is to verify among the typed objects touches each other, and if they can evolve or not. The objects are selected by the specialist and the search is accomplished by similarity in the *evolution cases database*. If the objects evolve, then the history is generated and stored in *history deforestation objects are: newobject*

(that is the identification of the new generated object), *objfather1*, *year1*, *type1* (information about the one of objects that evolves), *objfather2*, *year2*, *type2* (information about the other object that evolves), *result* (new resultant type), *newarea* (area composed by the two objects that evolved) and *yearresult* (year of evolution).

3.4 Results

3.4.1 Results in Vale do Anari

The Figure 3.5 presents a result of concentrations in *Vale do Anari*. To validate the system, we compared our results with the results of the structural classifier (SILVA *et al.*, 2008) as show in Figure 3.5. In static classification, the concentrations are presented in blue. In the CBR application the concentrations are presented in red. The CBR system, according to field work data, obtained 86% accuracy in the indication of concentrations. However, the concentrations of CBR highlighted in Figure 3.5, show improvements in results as of area. The concentrations of structural classifier highlighted in Figure 3.5 were not indicated by CBR because they have area smaller than 50 ha. In agreement with the *description rule* number 3, areas smaller than 50 ha do not indicate concentrations, and are not represented as such by the CBR system.

In terms of area, we analyzed 888 km² in *Vale do Anari*. Of these 888 km², 469 km² (52%) correspond to the deforested area, which 125 km² are land concentrations. In relation to the 469 km² of deforested area, 26% correspond to land concentrations area.

Furthermore, each concentration found by our system presents its history. An example of the history of some concentration land process is presented in Figure 3.6. The report generated by the system presents the evolution of objects, or its history. The objective of this analysis is to understand and describe the process of concentration pattern formation.

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Figure 3.5 – Concentrations of Vale do Anari.

The deforestation objects typed as *along the road* (300 - 1985, 368-1988, 537-1991) doesn't evolve in agreement with the evolution rule number 3 (*ER3 - A along the road object cannot be merged with other object*). In 1991 the deforestation object 372-88 (*small lot*) touch the deforestation object 524-91 (*small lot*) and merge in agreement with the evolution rule number 2 (*ER2 - Two small lots < 50 ha can be merged and the new object is a small lot*). The new object (1 - 1991) have a type *small lot*. In the same way in 1994 the deforestation object 523-91 touch the deforestation object 558-94 generating the new object 2-1994 with type *small lot*. The same rule is applied in 1997 with the merge of the objects 1-91 and 803-97 generating 3-97 and the objects 553-91 and 821-97, both with the type *small lot*. In 2000 the object 709 with the type *concentration* merge with the objects 1,2,3 and 765 in agreement the evolution rule number 5 (*ER5 - A small lot < 50 ha can be merged with a land concentration object and the new object is a land concentration*).

 1982 - 1985 1985 - 1988 1988 - 1991 1991 - 1994 1994 - 1997 1997 - 2000 								Unt		
	New Object	Father's Object 1	Туре	Year	Father's Object 2	t Object's _{Type}	Year	<i>tory</i> Result	New Area	Year
L	9	765	Small Lot	2000	8	Concentration	2000	Concentration	3356090,8977	2000
	8	7	Concentration	2000	4	Small Lot	1997	Concentration	3346262,9055	2000
	7	6	Concentration	2000	3	Small Lot	1997	Concentration	3252806,8508	2000
	6	5	Concentration	2000	822	Small Lot	1997	Concentration	2929175,7966	2000
	5	709	Concentration	2000	2	Small Lot	1994	Concentration	2919230,7888	2000
	4	821	Small Lot	1997	553	Small Lot	1991	Small Lot	93456,0547	1997
	3	803	Small Lot	1997	1	Small Lot	1991	Small Lot	323631 ,0542	1997
	2	523	Small Lot	1991	558	Small Lot	1994	Small Lot	173574,0388	1994
	1	372	Small Lot	1988	524	Small Lot	1991	Small Lot	315756 0464	1991

Figure 3.6 – Example of concentration history. (Continues)



Figure 3.6 - Conclusion.

The system identifies 33 land concentrations in *Vale do Anari*. With the histories and trajectories of each concentration we can answer some questions about the deforestation in settlements projects in Amazonia. The analysis indicates that 27 concentrations (81%) started its trajectory in 1988 and 1991 however, 13 concentrations were formed in 1997 (Figure 3.7). As we pointed out before, the 1995 deforestation rate was the highest annual rate measured by INPE for the whole Amazônia (29059 km²) and Rondônia State (4730 km²) (INPE, 2007) since 1988. This high deforestation rate can be the result of several economical and politic factors that influenced the illicit land market, favoring land concentration in agrarian settlement projects.



Figure 3.7 – Analysis of trajectories and concentrations in Vale do Anari.

The fact that only 3 trajectories of concentration started in 1985 may indicates a tendency that lands not occupied or cleared in the initial period of the settlement occupation can be more susceptible to the processes of concentration. Figure 3.8 presents the evolution of deforestation in agreement of the types of deforestation objects.



Figure 3.8 – Evolution of trajectories in Vale do Anari.

With the histories we also analyze the trajectory of each concentration. The predominant trajectories in *Vale do Anari* are presented in Table 3.2. The trajectories 1 and 2 correspond to 30% of the defined trajectories, being 15% each one. The trajectory 3 corresponds to 12% and the trajectory 4 to 9%.

	1985	1988	1991	1994	1997	2000	%
1		Small Lot	Concentration	Concentration	Concentration	Concentration	15,2%
2		Small Lot	Small Lot	Small Lot	Concentration	Concentration	15,2%
3			Small Lot	Small Lot	Concentration	Concentration	12,1%
4		Small Lot	Small Lot	Small Lot	Small Lot	Concentration	9,1%

Table 3.2 - Predominant trajectories of concentrations in Vale do Anari.

The trajectory 1 indicates that the land concentration in *Vale do Anari* starts very early. After 6 years, 15% of deforestation area represented land concentration process. The trajectories 2 and 3 indicate that 27% of deforestation area started in period 1994-1997. Annual estimates of the rates of deforestation in Brazilian Amazonia indicate a considerable increase in 1995

that does not occur again in subsequent years (INPE, 2007). The trajectory 4 indicates that 9% of the occupation area began in the period of 1988-1991 forming concentrations only in 2000. The other trajectories representing 49% of the total are presents in table 3.3

1985	1988	1991	1994	1997	2000	%
		Concentration	Concentration	Concentration	Concentration	6,1%
	Small Lot	Small Lot	Small Lot	Concentration	Concentration	6,1%
		Small Lot	Concentration	Concentration	Concentration	6,1%
					Concentration	6,1%
	Concentration	Concentration	Concentration	Concentration	Concentration	3%
		Small Lot	Concentration	Concentration		3%
		Small Lot	Concentration	Concentration	Concentration	3%
Small Lot	Small Lot	Concentration	Concentration	Concentration	Concentration	3%
			Small Lot	Concentration		3%
Small Lot	Small Lot	Small Lot	Small Lot	Concentration	Concentration	3%
		Small Lot	Small Lot	Small Lot	Concentration	3%
Small Lot	Small Lot	Small Lot	Small Lot	Small Lot	Concentration	3%

Table 3.3 – Other trajectories of concentrations in Vale do Anari.

3.4.2 Results in Machadinho D'Oeste

The Figure 3.9 presents the result of concentrations process in *Machadinho D'Oeste*. We compared our results with field work data collected by (SOLER *et al.*, 2009).



Figure 3.9 – Concentrations in Machadinho D'Oeste.

In *Machadinho D'Oeste* the CBR system, according to field work data, obtained 77% of accuracy in the indication of concentrations. Some concentrations close to urban centers were not pointed out during field work, because this information wasn't accessible, but the system detected them. From the total of 22 occurrences indicated by field work and presented in Figure 3.9, the CBR system detected 17 of them. However, those occurrences were verified in 2006, and our analysis finished in 2000.

We analyzed the whole area, 2129 km², in *Machadinho D'Oeste*. Of the 2129 km², 818 km² (38%) corresponded to deforested area, and 132 km² (16%) corresponded to land concentrations. This proportion was lower than the proportion estimated for *Vale do Anari* settlement (26%), showing the importance of the planning and the control in this kind of rural settlement.

The system identifies 44 land concentrations in *Machadinho D'Oeste*. The analysis indicates that 4 concentrations started their trajectories in 1985, 1988 and 1991. However, 24 concentrations process started between 1994 and 1997 (Figure 3.10).



Figure 3.10 – Analysis of trajectories and concentrations in Machadinho D'Oeste.

The Figure 3.11 presents the evolution of deforestation in agreement of the types of deforestation objects.


Figure 3.11 – Evolution of trajectories in *Machadinho D'Oeste*.

The predominant concentration trajectories in *Machadinho D'Oeste* are presented in Table 3.4. The trajectories 1 correspond to 23% of the total trajectories defined. The trajectories 2 and 3 corresponds to 18% of the trajectories, being 9% each one. The trajectories 4 e 5 corresponds to 14%, being 7% each one.

Table 3.4 – Predominant trajectories of concentrations in *Machadinho D'Oeste*.

	1985	1988	1991	1994	1997	2000	%
1		Small Lot	Small Lot	Small Lot	Concentration	Concentration	23%
2	Small Lot	Small Lot	Small Lot	Concentration	Concentration	Concentration	9%
3			Small Lot	Small Lot	Small Lot	Concentration	9%
4		Concentration	Concentration	Concentration	Concentration	Concentration	7%
5			Concentration	Concentration	Concentration	Concentration	7%

The trajectory 1 indicates that the mostly of land concentrations, 23% started in period 1994-1997. The trajectory 2 indicates that 9% of the concentrations started in the period of 1991 to 1994, more than 9 years after the beginning of

the occupation. The trajectory 3 indicates that 9% of the concentrations started in 1997-2000. The trajectories 4 and 5 indicate a new process that started as concentration in the beginning and are equivalent to 14%.

The other trajectories found are presents in table 3.5

1985	1988	1991	1994	1997	2000	%
Concentration	Concentration	Concentration	Concentration	Concentration	Concentration	5%
Small Lot	Concentration	Concentration	Concentration	Concentration	Concentration	5%
Small Lot	Small Lot	Concentration	Concentration	Concentration	Concentration	5%
		Small Lot	Concentration	Concentration	Concentration	5%
		Small Lot	Small Lot	Concentration	Concentration	5%
			Small Lot	Small Lot	Concentration	5%
				Small Lot	Concentration	5%
Small Lot	Small Lot	Small Lot	Small Lot	Concentration	Concentration	2%
	Small Lot	Concentration	Concentration	Concentration	Concentration	2%
	Small Lot	Small Lot	Concentration	Concentration	Concentration	2%
	Small Lot	Small Lot	Small Lot	Small Lot	Concentration	2%
Small Lot	Concentration	2%				
	Small Lot	Small Lot	Small Lot	Small Lot	Concentration	2%

Table 3.5 – Other trajectories of concentration in Machadinho D'Oeste.

In *Machadinho D'Oeste* the trajectories of concentration starting in 1985 are greater than in *Vale do Anari* and 29 trajectories (65%) started until 1991. However, only in 1997 and 2000 a large number of concentration lands was

detected. This behavior was similar to that one observed in *Vale do Anari* for the period of 1994 to 1997. This period correspond to the high deforestation rate detected by INPE. The main difference was that *Machadinho D'Oeste* in the subsequent period didn't show a significative reduction, showing that the land concentration process kept on there.

Machadinho D'Oeste is a planned settlement project (BATISTELLA, 2001; ESCADA, 2003) and in the beginning of its implantation INCRA must have controlled and monitored the lots more than in *Vale do Anari*, named as a Rapid Settlement Project, created to reduce land conflicts and to settle landless people from other regions (SEDAM, 1996). After 1994, the deforestation rate increased and *Machadinho D'Oeste* concentration results suggest that INCRA lost control and the concentration process started to occur more intensely.

4 CONCLUSIONS

This thesis presents a method for eliciting the evolution of geospatial objects. This evolution process is analyzed to understand the conditions that define how and when an object changes its properties. Our research is based in the development of a Case-Based Reasoning system that describes how geospatial objects evolve.

We are interested in evolving objects specifically in cases where the simple rules of merging and splitting are not enough to describe their evolution, since such evolution depends on their types. We propose a method that uses previous cases and expert knowledge from the specific domain as the main sources of knowledge used to solve new problems. The main contribution of our research is the definition a of Case-Based Reasoning (CBR) method to describe the object's type and find out how geospatial objects evolve.

The approach uses a Case-Based Reasoning technique that provides mechanisms to define evolution meaning and constraints and extracting cases of changes. Therefore, our approach allows to store and to retrieve evolution object's history.

Experimental results for the Amazonia Region corroborate with the effectiveness of our proposal. Using CBR system for describing object evolution follows the work of Silva et. al. (2008) 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 advances on this question by addressing the problem of tracking changes during an object's lifetime, based on type-specific evolution rules. In our experiments using the Case-Based Reasoning (CBR) technique, we were able of to obtain the rules for object evolution and describe how geospatial objects evolve. This CBR technique proved to be a simple and useful approach to set up the rules for land change evolution.

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In our application domain, CBR presented a satisfactory result, since the knowledge base had only a few cases, which were presented to experts 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 be slow performance. In such cases, the CBR system 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 software packages do not provide adaptation and learning resources. They simply recover the most similar case and make the solution available for the specialist determining if it solves his matching problem.

Our experience shows that CBR-based techniques are useful and simple to set up in an evolving geospatial problem when there are few types and clear-cut rules. When there are many types and complex evolution rules, the CBR system 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 system we designed to be promising. We suggested to analyze the history of the deforestation objects in order to find an evolution pattern. Looking at the pasted is possible to predict the future and to find measures to minimize the process of deforestation in the Brazilian Amazonia. Our work also indicates the need for integration of the CBR system developed with geostatistical tools and data mining system to automate, in any way, all tasks involved in the overall process.

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ANNEX A – CBR SYSTEM: IMPLEMENTATION ASPECTS

This annex presents the implementation aspects of this work. We built CBR Prototype using Borland Delphi 7.0, Interbase database and Shape Viewer Objects (SVO), a native set of Borland Delphi components for creating GIS mapping software. Section A.1 presents the CBR prototype.

A.1 CBR SYSTEM

Figure A.1 shows de CBR cases database. The cases are mapped from model representation described above to a set of normalized tables in Interbase relational database. The descriptive part of knowledge – descriptions and evolution rules – has been represented in the tables of the database system.

		CASE		PATTERN	CONTEXT	TYPES		
		•	1	Geometric	Indifferent	Concentration		
			2	Irregular	Touch road	Along road		
			3	Irregular	Don't touch road	Small lot		
			4	Linear	Touch road	Along road		
		and a	5	Linear	Don't touch road	Small lot		
			E	Evolution	Cases Databas	e	_	
ASE	OBJECT1		E	Evolution	Cases Databas	e Area2	EVOL	VENEWTYPE
ASE	OBJECT1 1 Concentra	tion	E	Evolution (Cases Databas	e AREA2 Indifferent	EVOL T	VE NEWTYPE Concentration
ASE	OBJECT1 1 Concentra 2 Along the I	tion	E	Evolution (AREA1 Indifferent Indifferent	Cases Databas OBJECT2 Concentration Indifferent	e AREA2 Indifferent Indifferent	EVOL T F	VE NEWTYPE Concentration
ASE	OBJECT1 1 Concentra 2 Along the 3 Small Lots	tion Road	E	Evolution (AREA1 Indifferent Indifferent Indifferent	Cases Databas OBJECT2 Concentration Indifferent Small Lots	C AREA2 Indifferent Indifferent Indifferent	EVOL T F T	VE NEWTYPE Concentration Small Lots
ASE	OBJECT1 1 Concentra 2 Along the 3 Small Lots 4 Small Lots	tion Road	E	AREA1 Indifferent Indifferent Indifferent S0	Cases Databas OBJECT2 Concentration Indifferent Small Lots Concentration	C AREA2 Indifferent Indifferent Indifferent Indifferent	EVOL T F T T	VE NEWTYPE Concentration Small Lots Concentration

Figure A.1 – Description and evolution cases database

The data input screen is shown in Figure A.2. The shapes with the geospatial objects are loaded by the system with their attributes that will be used to compose the new case.



Figure A.2 - Data input screen.

The module type carries the attributes of the objects and it accomplishes the search of the similar case in the database to define the type of the objects (Figure A.3). The similarity can be calculated globally for a case, for example, counting the attributes of the case which have equal values, or locally considering similarity among the values of an attribute. In our domain application we searched only the same cases, in other words, totally similar, and the search for attributes with equal values is done through a SQL (Structure Query Language) query.



Figure A.3 – Defining typed objects

After defining the type of all objects, the module evolution verifies among the typed objects touches each other, if they can evolve or not (Figure A.4). The search is accomplished on the evolution database of the same way as in module type.

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Object 1 42 Concentration 1998 Object 2 497 Concentration 1991
Evolve YES
Result Concentration
x : 590774,20323 Y : 8899428,05686

Figura A.4 – Defining evolution objects

If the objects evolve, their history is generated and stored in the history database for later recovery. Figure A.5 shows typed and history databases.

		IDOB	JECT YEARS	TYPES	AREA		
			55 1985	Along the Road	9148719,96		
			42 1988	Concentration	693630,002		
			43 1988	Small Lot	39384		
			341 1988	Small Lot	54738,0078		
			355 1988	Small Lot	7064,9961		
			358 1988	Along the Road	10656,0078		
			478 1991	Small Lot	12456		
			497 1991	Concentration	781884		
			486 1994	Concentration	3093893,5		
		100	507 1994	Small Lot	32103 0078		
			History C)biects Dat	abase		
NEWOR IECT	OR IFATHER1		History C	bjects Dat	abase		
NEWOBJECT	OBJFATHER1	YEARFATHER1	History C)bjects Dat	abase	YEARRESULT	NEWAREA
NEWOBJECT 3001 3002	OBJFATHER1 478 497	YEARFATHER1 1991	History C	Dbjects Dat	abase RESULT Small Lot	YEARRESULT 1991	NEWAREA 67194,0078
NEW0BJECT 3001 3002 3003	0BJFATHER1 478 497 486	YEARFATHER1 1991 1991	History C	Dbjects Dat YEARFATHER2 341 1988 42 1988 43 1988	Abase RESULT Small Lot Concentration	YEARRESULT 1991 1991	NEWAREA 67194,0076 1475514,002 3132277
NEWOBJECT 3001 3002 3003 3004	DBJFATHER1 478 497 486 507	YEARFATHER1 1991 1994	History C	YEARFATHER2 341 1988 42 1988 43 1988 002 1991	Abase RESULT Small Lot Concentration Concentration	YEARRESULT 1991 1991 1994 1994	NEWAREA 67194,0076 1475514,002 3133277,5 1507517,0098
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Figure A.5 – Typed and history databases