Multi-Agents Systems for Cartographic Generalization: Feedback from Past and On-going Research

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Multi-Agents Systems for Cartographic Generalization: Feedback from Past and On-going Research

Technical report, IGN France, LaSTIG - COGIT team

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Preamble - Jan. 2018
This report was first prepared for a book publication back in 2010. The book project was finally canceled years later, and this paper was never published. In early 2018, it was decided to publish it online as a research report, and the text was slightly updated. But most of the papers related to agent-based map generalisation are not included and discussed in this report.

Abstract

Cartographic generalization is a highly local and contextual process where decisions are taken locally to better adjust the transformations used to the local geography. Thus, cartographic generalization fits well with the multi-agents paradigm that promotes decentralized and autonomous decision-making. The past years of research in cartographic generalization showed several successful attempts to use multi-agents systems, and this paper provides a feedback on these attempts. We extracted a core modeling of a multi-agents system for generalization and highlighted its main components. Previous propositions of multi-agents generalization processes are described in relation to this core modeling, and feedbacks from experimentations with these processes are discussed to define a research agenda in multi-agents modeling for generalization.

1 Introduction

This paper proposes a feedback on the use of multi-agent approaches for cartographic generalization. Several research studies made these last twenty years in automated generalization rely on this approach [Baeijs et al., 1996], [Ruas, 1999], [Lamy et al., 1999], [Galanda and Weibel, 2002], [Duchêne, 2003], [Jabeur et al., 2003], [Gaffuri, 2007], [Sabo et al., 2008], [Zhang and Guilbert, 2011], [Renard and Duchêne, 2014], [Maudet et al., 2014]. Some of them have also been successfully used for production. Basing especially on the studies we have been involved in, we identify the components that are needed in a generalization model based on the multi-agents approach, and draw lessons on the relevance of this approach for generalization. In this paper, we use the classical terms Digital Landscape Model (DLM) and Digital Cartographic Model (DCM) introduced by Grünreich [Grünreich, 1985]. A DLM is a geographic database where geographic features are "in place", while a DCM is a geographic database where the objects have been distorted to cope with a given symbolization. We name "classical topographic DLM to DCM problem", the classical generalization problem encountered by the National Mapping Agencies (NMAs) that consists in deriving, from a topographic DLM, a topographic DCM having a lower level of detail but the same data model (no model generalization). In other words, the intended symbolization scale of the DCM belongs to the scale range that can be obtained from the DLM without any model generalization. The paper is organized as follows. Section 2 goes back over the "lineage" of the multi-agent based approaches for generalization. Section 3 identifies the components necessary for a multi-agent based generalization while trying to connect them to modeling elements already identified in previous generalization frameworks. Section 4 presents an overview of several multi-agent approach implementations in which we have been involved. Basing in these experiments, section 5 discusses the characteristics, advantages and limits of the multi-agent modeling for automated generalization, and defines a research agenda. Finally, section 6 concludes and draws some perspectives.

2 From Step by Step, Knowledge Based Approaches to Multi-Agent Approaches

2.1 Step by Step, Knowledge Based, Local Approach

Most of the agent based generalization approaches have their origin in the step by step, knowledge based, local approach initially proposed by [Brassel and Weibel, 1988], [Mcmaster and Shea, 1988]. In these approaches, the generalization process consists in progressively transforming the objects by means of generalization algorithms. These algorithms are chosen and applied locally according to the cartographic conflicts to solve. Moreover, these generalization processes take into account the identified objectives (or specifications) of the target generalized data. Beard [Beard, 1991] proposes to represent explicitly these specifications by constraints. Generalization is seen as a constraint satisfaction problem - the constraints guide the process. Ruas and Plazanet [Ruas and Plazanet, 1996] propose to use geographic object constraint violation values to monitor the generalization. They also propose to let the generalization process operate at different levels (object, group of objects, part of object), and with cycles including choice of algorithm, actual transformation and validation. The matching between a constraint violation and possible generalization algorithm to correct it can be expressed by rules and the generalization is then managed by an expert system [Nickerson, 1988], [Mackaness and Fisher, 1987], [Buttenfield and Mark, 1991].

2.2 Why to Use Multi-Agent Approaches for Generalization?

The multi-agent paradigm appeared in the 1990's. This approach federates the object oriented approach and the expert systems. Weiss [Weiss, 1999], defines an agent as an entity that has a goal and acts autonomously in order to reach this goal thanks to capacities of perception, deliberation, action, and possibly communication with other agents. A multi-agent system is a set of interacting agents. Multi-agent systems are used in complex systems simulation and also for complex problems solving. The power of this approach is to distribute the complexity among a set of relatively simple interacting agents instead of using a single central intelligent system dealing with the whole complexity. Each agent has limited capacities of perception and action toward the problem to solve, but the complexity emerges from the agent actions and their potential interactions. The agent paradigm is particularly adapted to problems that are naturally distributed and hard to solve in a centralized approach. Because generalization is a complex problem distributed over the geographic space, the multi agent paradigm seems rather adapted to generalization. In the step by step knowledge based local approach, the generalization is seen as a set of local actions applied to progressively solve local conflicts. Using a multi-agent approach for generalization can be considered as a "natural" evolution of this approach.

2.3 Geo-Agents for Generalization

In generalization multi-agent based approaches, the local transformations are seen as actions performed by the agents on themselves depending on what they perceive from their context. The agents are used to model the geographic features of the Digital Cartographic Model being generalized: a single object, a group of object, a part of object or a point. That way, the geographic features generalize themselves, seeking for a solution that is satisfying at a collective level.

3 Components of a Multi-Agent Based Generalization Model

Figure 1 shows the "brain" of a geographic agent for generalization. This brain is decomposed into three main kinds of components: its capacities, its mental representation of the world and himself, and its knowledge. The figure also shows the common resources shared by the agents. Sections 3.1 to 3.5 describe each of these components.

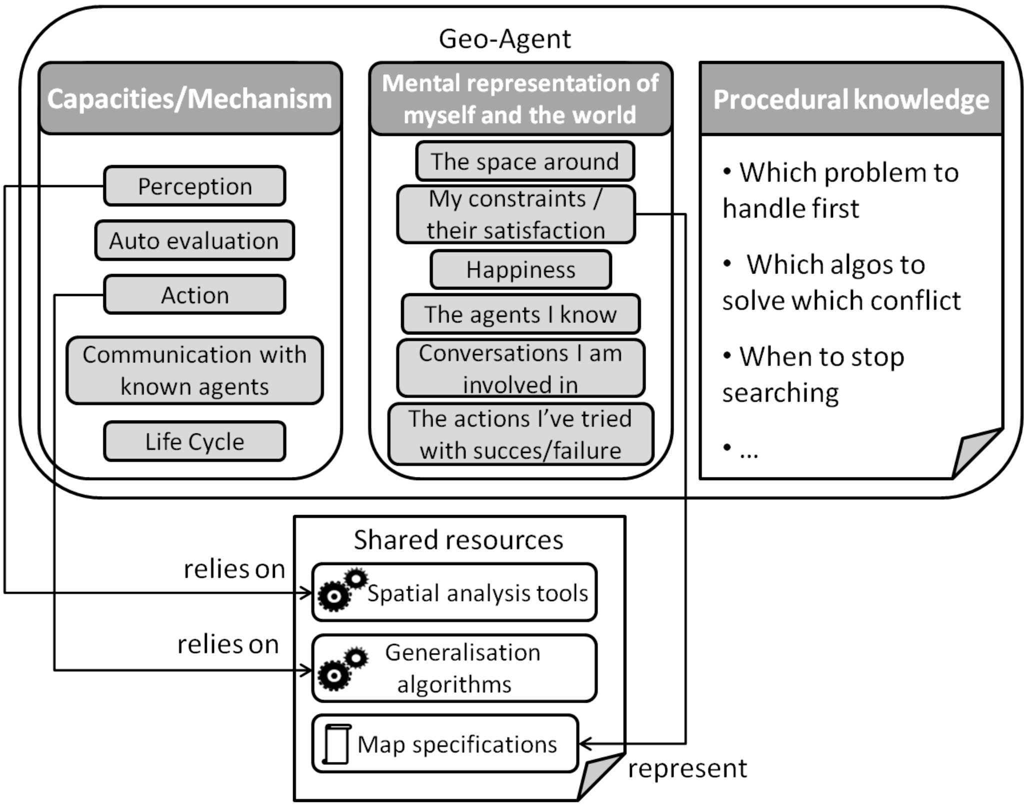

Figure 1: Modelling of a geo-agent in our multi-agent generalization approach.

3.1 Capacities

Agents usually have capacities of perception, deliberation, action and communication. These capacities can be more or less developed depending on the purpose each agent is designed for. For a generalization agent, the required capacities are the following:

- **Perception**: the agent needs to perceive its own state and also the state of its surrounding space. Neighboring agents that can influence each other because they share constraints have to be aware of their mutual existence. Such perception capacity requires spatial analysis methods. Spatial analysis methods have been identified by [Shea and Mcmaster, 1989] as a key component in generalization. For instance, building block agents are able to compute Delaunay triangulation between their components to identify proximities and congestions [Ruas, 1998]. These methods are embedded in the agent's perception capabilities.

- **Self-evaluation**: based on its perception, the agents need to be able to analyze how far they are from a well-generalized state. The analysis is performed by computing constraints satisfaction values, and aggregating these values to have an overall numeric evaluation of the agent's state. The self-evaluation capacity is also useful for assessing an evolution of the agent status (*i.e.* the evolution between before and after an action application, in order to validate the action). The "Structure recognition" step of [Brassel and Weibel, 1988] is carried out by the perception and self-evaluation capacities of the agent.

- **Action**: of course, the agents need to act in order to improve their state. These actions are mainly geometrical transformation operations. Other possible actions a decomposition into parts, or an aggregation with other agents. Such operations also require spatial analyses methods.

- **Communication and interaction**: the geo-agents may simply interact through mutual influences or forces (*i.e.* point agent interaction in GAEL, see 4.3) or communicate in evolved ways by exchanging messages. Communication may be used to encourage an agent to do something (*i.e.* an action to solve a common problem) or to inform another agent of a

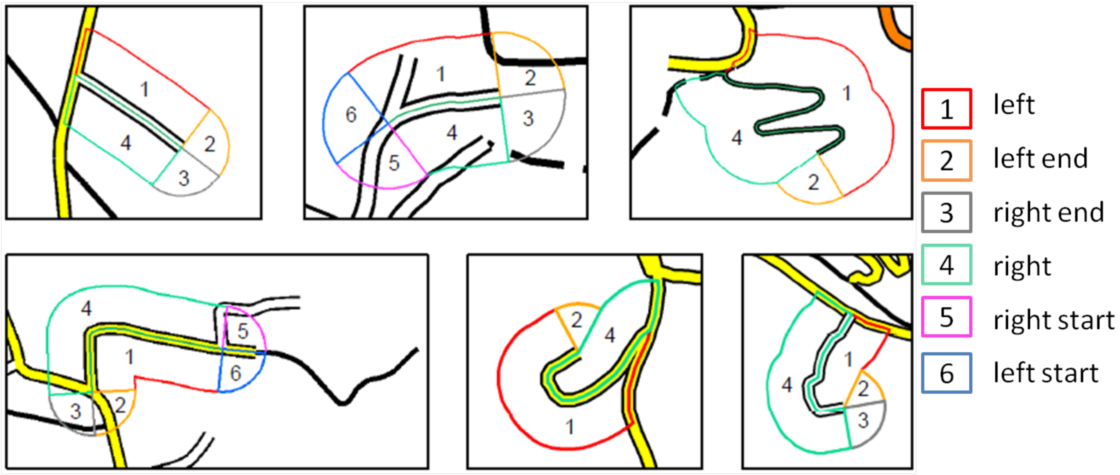

Figure 2: How dead end road agents model space around them for several instances [Duchêne, 2004].

particular fact so that it might update its mental representation of the world (*i.e.* an agent is informed by a neighbor agent that it eliminated itself which changes the situation around).

- **Life cycle**: the geo-agents generic behavior is integrated in their life cycle that sequences the perception, self-evaluation, action and communication steps. The life-cycle integrates the decision-making capacities of the agents and is guided by procedural knowledge. The life cycle particularly encapsulates the trial/error mechanism required by [Ruas and Plazanet, 1996], *i.e.* an agent tries an action, evaluates its effect, and tries another one or backtracks if the action aggravated the situation.

3.2 Mental Representation

Following the principles of the constraint based generalization approach [Harrie and Weibel, 2007], the agents have a mental representation of the constraints they aim at satisfying. The agents' perception capacities that use spatial analysis tools allow filling this representation with current values of the constraints (*e.g.* building current granularity is 0.05 map mm). The agents' auto-evaluation capacities allow to compute the constraints satisfaction as a part of the mental representation (*e.g.* if building current granularity is 0.05 map mm, the auto-evaluation capacity helps to represent granularity constraint satisfaction as 'not satisfied'). The geo-agents may also be able to represent space around them with abstraction. It may help the agent to evaluate some constraints. For instance, Figure 2 shows the dead end agent mental representation of the space around him. Thanks to this abstraction, it is able to evaluate if a building is still in the right end corner of his space representation in order to satisfy a relative positioning constraint. The environment in a multi-agents system is the set of all elements that are not agents in the system, but which surround the agents and interact with them. To allow this mental representation of space around (*i.e.* the environment) by the agents, the environment has to be formalized to give the agents a topology and a position in space [Ricci et al., 2010], [Mathieu et al., 2014], which is done by using the GIS capabilities of our systems.

The agent happiness corresponds to the closeness to his own goal. It is computed thanks to his auto-evaluation capacity and may be used to make decisions during the agent life cycle. But the agent happiness may also be used to monitor the generalization process either by some other agent or a dedicated entity of the system. The other agents a geo-agent knows about may be peers, *e.g.* buildings for a building agent, components of the agents, *e.g.* roads and buildings for block agent (Figure 3), or a container agent when the agent is the component of a higher level agent (a city for a block agent).

A geo-agent is able to communicate through messages with the agents he knows and though keeps traces of the unfinished conversations: he knows if he is waiting for an answer or if he has to answer to known agent. For instance, if a road agent has been asked to move by some other agents, he first needs to store the conversations, then analyze its situation before answering he accepts to move or not. Finally, the agent is able to store the actions he has tried and if they have

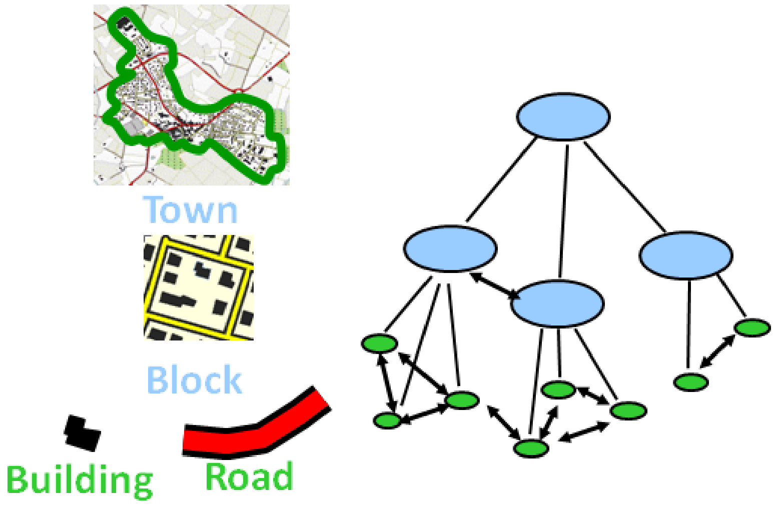

Figure 3: Three ways to know other agents for a geo-agent: a peer, a component or a container.

succeeded or failed. It helps the agent to avoid keeping on trying a failing action. It also helps the agent to update his procedural knowledge that guide the choice of the best action to try in a given situation.

3.3 Procedural Knowledge

Procedural knowledge was defined by [Armstrong, 1991] as the knowledge "which is necessary to select appropriate operators for performing generalization tasks". In the agent context, this knowledge are the knowledge used by an agent to choose how acting at a given moment of the generalization process. Procedural knowledge is included in the “controls” of Brassel and Weibel [Brassel and Weibel, 1988] and the “Computational elements” and “Transformation controls” of McMaster and Shea [Mcmaster and Shea, 1988], [Shea and Mcmaster, 1989] (choice of an operator, an algorithm, and parameters) are part of it. The procedural knowledge can be defined per agent, or shared by all the agents of the same kind (*e.g.* all of the building agents have the same procedural knowledge). Generalizing an area with poor procedural knowledge can lead to non-satisfactory generalization results or/and take too much time to be acceptable. Defining and maintaining good procedural knowledge is thus very important. Unfortunately, transferring the knowledge used by the cartographic expert to generalize data into generalization systems is a complex task [Rieger and Coulson, 1993], [Weibel et al., 1995], [Kilpelainen, 2000]. Moreover, knowledge has to be regularly updated in order to take new elements (*e.g.* new generalization operations) into account or new user needs (*e.g.* modification of the map specification). In Section 4.4, we present an approach to automatically revise procedural knowledge.

3.4 Resources Shared by the Agents

Some resources are not specific to one agent but are shared by all the geo-agents. First, some tool libraries are made available to allow the agents perception and action capacities (Figure 1). The spatial analysis tools allow the agent to perceive its environment through measures such as its distance to another object and structures such as triangulation to measure proximities. The spatial analysis tools allow the “structure recognition” in [Brassel and Weibel, 1988] and correspond to “spatial and holistic measures” in [Shea and Mcmaster, 1989]. The agents also share generalization algorithms on which the actions rely to transform the agent and satisfy its constraints (Figure 1). The more algorithms the library contains, the more effective the generalization is, as the agent can really adapt its generalization to its context. The generalization algorithms correspond to “process library” in [Brassel and Weibel, 1988] and “spatial and attribute transformations” in [Shea and Mcmaster, 1989]. Finally, the agents also share common knowledge on map specifications. Map specifications gather cartographic legibility and map objectives and are translated into constraints and satisfaction methods. It corresponds to the “controls” of [Brassel and Weibel, 1988] and gathers the “Theoretical elements”, “Application-specific elements”

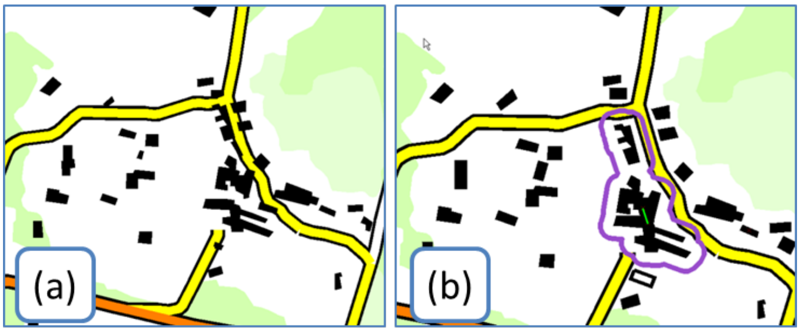

Figure 4: (a) initial data. (b) generalization with a conflicting area emerging in the middle..

of [Mcmaster and Shea, 1988] and the "Geometric conditions" of [Shea and Mcmaster, 1989].

3.5 Other Components of the System

Additional components are necessary to allow the agent-based generalization besides the geo-agent and the shared resources. First, a scheduler agent is required to decide which agent to activate at a given step of the generalization process. Depending on the scheduling strategies, the results may drastically differ [Duchêne, 2004]. Moreover, in order to improve geo-agents procedural knowledge, a machine learning and knowledge management component is necessary. Although the improvement is not mandatory to provide generalization results, such a component has proven very useful to improve the efficiency and effectiveness of our agent-based system. Finally, a system to identify emerging conflicting areas can be useful to optimize the quality of generalization results. In this iterative process, close unsolved conflicts might occur and the agents will not be able to solve them (Figure 4), unless there is a change of perspective: only by treating the conflicting agents as a group, we can clean the area. Emergence in multi-agents systems [Müller, 2004] is the appearance of a higher level entity from the behavior of lower level entities, identified by an observation on a long period of time.

4 Implementations of the Multi-Agent Approach in Generalization at IGN

As an illustration of the principles presented in the previous section, this section presents four agent based generalization models dedicated to different application contexts. One associated model for the automated revision of the control knowledge is also presented, and finally an overview of agent based generalization systems used in research or production is given.

4.1 AGENT

The AGENT model has been proposed by Ruas [Ruas, 1999] and then used and refined in a European project named AGENT [Barrault et al., 2001]. It translates the model by Ruas and Plazanet [Ruas and Plazanet, 1996] (possibility to focus on objects, groups or parts of objects, expression of the constraints on each object, see section 2) into a multi-agent paradigm, while extending it. Three levels of geographic agents are considered. *Micro* agents correspond to single geographic objects. *Meso* agents correspond to groups of objects and can be nested: a town (*meso*) is composed of building blocks (*meso*), in turn composed of buildings (*micro*). *Macro* agents correspond to entire populations of geographic objects (all roads, all buildings) and are used to monitor indicators like the quantities of objects by theme in the DCM.

Each agent has a representation of its constraints and their satisfaction in the form of a set of constraints objects (in the computer science meaning), each constraint object being in charge of monitoring a given constraint of the agent and proposing possible actions (generalization algorithms) to improve its satisfaction. The life-cycle of the geographic agent consists in assessing its constraints, choosing and trying an action among the ones identified by its constraint objects, evaluating the progression, committing or backtracking the action, and so on until it reaches a perfect

Figure 5: Generalization of topographic data from the IGN France BD Topo® database (reference scale 1:15 000) to a 1: 50 000 map. Result obtained with the AGENT model [Barrault et al., 2001].

state or no more action can be tried. A depth first mechanism including backtracking enables to temporary accept less good solutions on the way to the best possible one. An agent knows the meso agent it is a component of, and meso agents also know their components. Communications are hierarchical: meso agents trigger their components, can give orders to them or change the target satisfaction of their constraints [Ruas, 2000].

The AGENT model has successfully been applied to the generalization of data having a hierarchical structure, like urban zones in the "classical topographic DLM to DCM problem" at medium scales (with a hierarchy of buildings, building blocks and town). Mountainous roads have also been successfully handled with this model because they can be generalized by being decomposed into homogeneously coalesced parts (the hierarchy is then part of road, road). Figure 5 shows examples of results obtained with the AGENT model.

4.2 CartACom

The CartACom model [Duchêne, 2003], [Duchêne, 2004] is dedicated to the expression and resolution of relational constraints, defined as constraints on a relation between two agents (**e.g.** proximity, relative orientation). While in the AGENT model, constraints concern one agent (and constraints concerning two agents are expressed and solved at the level of the meso agent they belong to), in the CartACom model constraints can be shared by two agents, represented and solved at the level of these agents. A CartACom agent perceives a portion of space around itself in order to identify its neighboring agents and the constraints shared with them. The representation of constraints of the AGENT model has been extended to deal with relational constraints. When necessary to assess its constraints, an agent has an explicit modelling of the space around him, e.g. the dead ends in networks have an explicit representation of their left and right sides (see figure 2, section 3.2). A CartACom agent knows all agents with which it is sharing a relational constraint. As actions, on top of being able to apply a generalization algorithm to itself, a CartACom agent can also ask an agent with which it is sharing a constraint to apply a given generalization algorithm to itself. The CartACom agents have therefore communication capacities, in order to send requests of actions to their neighbors, answer to such requests, and send information on their own modifications. Their life-cycle includes a stage where the agent handles its received messages and a stage where it handles its relational constraints in a way similar to the AGENT life-cycle. The life-cycle is interrupted when the agent sends a request for action to another agent, until an answer is received. A hook to the AGENT model enables the CartACom agent to also handle its internal constraints, but the AGENT life-cycle is seen as a black box from the CartACom life-cycle. The CartACom life-cycle also provides an observation mechanism to stop the process when conflicting areas emerge (Section 3.5) [Duchêne and Touya, 2010].

The CartACom model has been successfully applied to the generalization of rural zones in the "classical topographic DLM to DCM problem" at medium scales (figure 6).

4.3 GAEL

Spatial data are usually represented as objects and fields. Object representation is suitable for well delimited entities, like buildings and roads, while fields represent distributed phenomena, like the relief and the land use cover. The GAEL model [Gaffuri, 2007] introduces fields into the

Figure 6: Generalization of topographic data from the IGN France BD Topo® database (reference scale 1:15 000) to a 1: 50 000 map. Result obtained with the CartACom model [Duchêne, 2004].

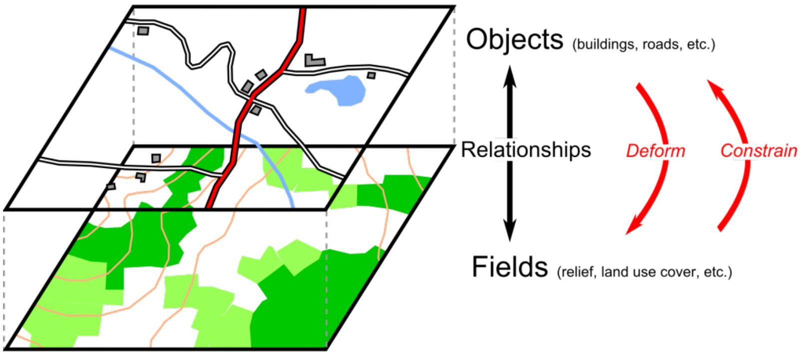

Figure 7: Relationship between the usual geo-agents and the field in GAEL.

generalization process by enabling field-object relations preservation. For example, river objects outflow on the relief field has to be preserved. The GAEL model is composed of two components:

- A field-object interaction model [Gaffuri, 2008]: Fields are agents; they have their own generalization constraints to satisfy. CartACom relational constraint model is extended to relational constraints between objects and fields. Objects perceive the state of their relation with the fields, and fields also perceive how the objects above them evolve. Field-object relational constraints are satisfied by enabling field-object interactions: fields constrain object transformations, while objects trigger local field deformations (Figure 7).
- A deformation model [Gaffuri, 2009]: In order to introduce local deformations into the generalization process, fields can become deformable. These deformable agents have the capability to decompose themselves into small parts (points, segments, and triangle) and instantiate some suitable constraints on these parts depending on the purpose of the deformation. The local deformation is obtained with progressive points displacements using an agent-based engine: each point is an agent, whose purpose is to balance constraints instantiated on the small parts it belongs to. This physical approach is comparable to the one used by [Baeijs et al., 1996], and [Bader et al., 2005]. This deformation model is generic and has been specialized for other generalization cases where deformations are required [Gaffuri, 2009].

The GAEL model has been applied to relations between rivers, buildings and the relief. Now, during the generalization process, buildings and rivers can deform the relief under them to preserve respectively their elevation value and their outflow.

4.4 RevK

As introduced in Section 3.3, the agent approach is based on the use of procedural knowledge. The choice of this knowledge has a deep impact on the generalization results. Unfortunately, most of the time, knowledge definition and evaluation are fastidious. In order to tackle this issue, we propose a general approach, illustrated in Figure 8, based on the offline revision of the procedural knowledge: a diagnosis agent has for role to detect, during the normal use of the generalization system, if the procedural knowledge needs to be revised [Taillandier, 2008], [Taillandier and Taillandier, 2012]. If the agent detects a defect of the procedural knowledge, an offline revision process is triggered.

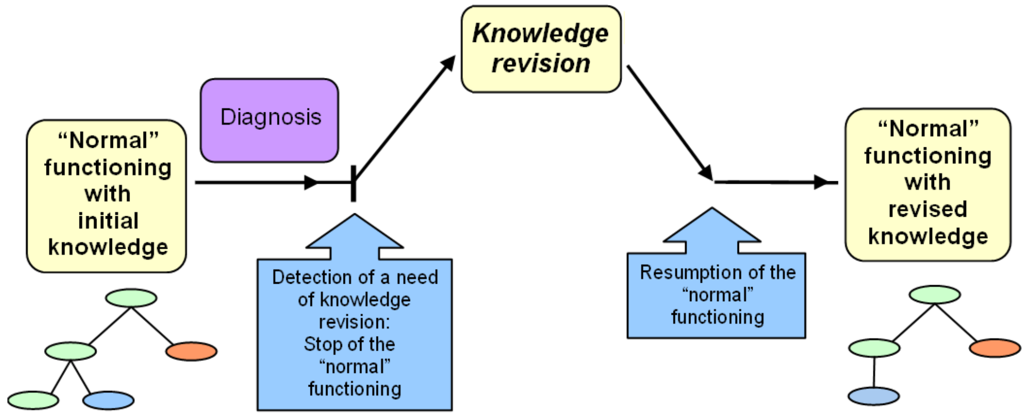

Figure 8: General approach of RevK.

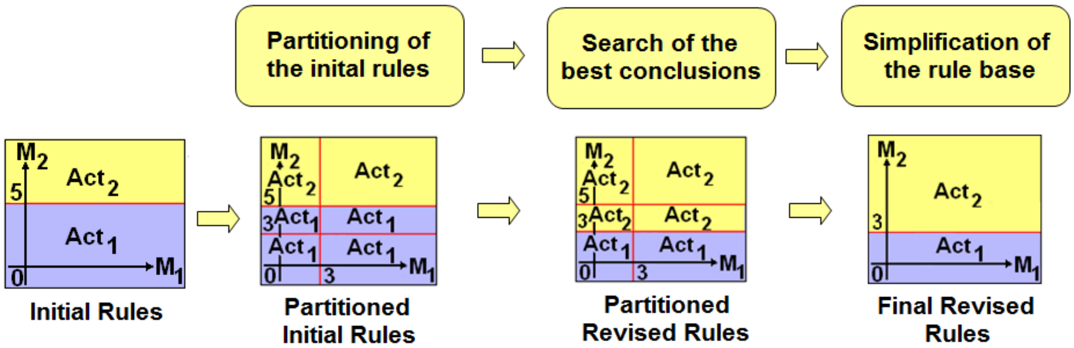

Figure 9: Approach for production rule revision.

In [Taillandier et al., 2008], we proposed an approach allowing the revision of the procedural knowledge of generalization systems based on the exploration of search trees (such as the AGENT model). Our approach is composed of two stages:

1. Exploration stage: generation of experience,
2. Analysis stage: revision of the procedural knowledge from experience.

The exploration stage consists in selecting a sample of geographic objects (called revision sample) and in generalizing them with a specific procedural knowledge, the "minimal" knowledge. This knowledge allows to build all the existing states when generalizing a given object. The analysis stage consists in revising the procedural knowledge from the analysis of the revision sample. In this context, we propose an approach, dedicated to the revision of knowledge expressed by production rules, composed of 3 steps (Figure 9). The first one consists in using the information contains in the revision sample in order to deduce a partitioning of the initial rules. Each rule is thus decomposed in a set of sub-rules, each representing an area in which the system has a homogeneous behavior. The second step consists in searching the best conclusion to assign to each sub-rule. For this step, we proposed to use local search techniques. The last step consists in simplifying the rule base obtained in order to improve its readability and its generalization power.

4.5 CollaGen

As it is partly illustrated by the previous parts, many automatic generalization processes have been developed, but are only relevant for a limited part of the generalization problem, in terms of landscape or theme. AGENT is completely effective on urban areas and mountain roads while CartACom is relevant for rural areas for instance. CollaGen [Touya et al., 2010] seeks to benefit from the rich diversity of available (agent based or not) processes by making them collaborate to generalize a complete map: data is partitioned into geographic spaces which are generalized by the most adapted available process (*i.e.* AGENT for urban areas).

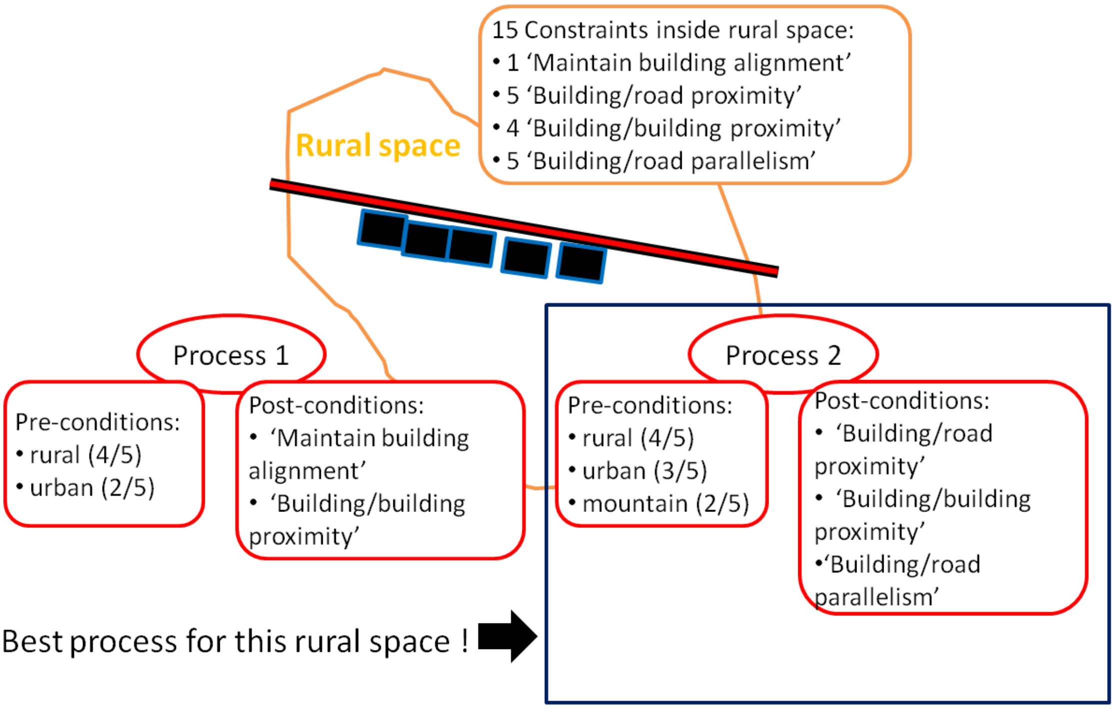

Figure 10: The best process to generalize this rural space according to the constraints contained in it depends on the adequacy to the Post-condition constraints.

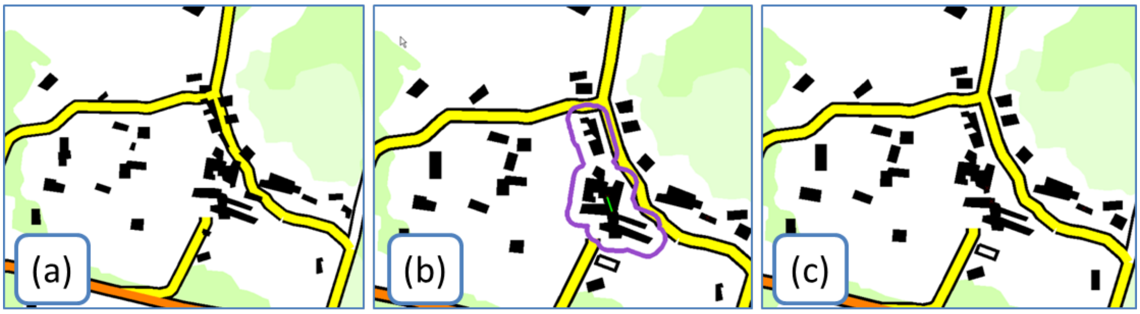

Figure 11: (a) initial rural space. (b) Conflict cluster emergence during a CartACom process. (c) A least-squares process is chosen to solve the conflict cluster.

In CollaGen, the geo-agents are the geographic spaces (urban areas, rural areas, the road network, etc.). As the geographic objects contained in a space are not necessarily generalized with agent-based processes, they are not considered as agents but are parts of the environment the space agents can perceive. For the same reason, the constraints are externalized as shared resources accessible to the space agents that contain the objects constrained. The actions of space agents are generalization processes rather than simple algorithms. In CollaGen, the shared resources are formalized to allow the interoperability between processes that were not designed to collaborate [Touya et al., 2010]. Notably, generalization capabilities are formally described to know the spaces that can be relevant ('Pre-conditions') and the constraints that are a priori satisfied after generalization ('Post-conditions'); it helps to choose the best process to generalize a given space (Figure 10).

CollaGen also provides an observer agent that is able to pause the system when a cluster of unsolved conflicts emerges in a geographic space. Then, a different process is searched to deal with the emerging conflicts, and when this local solving is done (Figure 11), the generalization of the geographic space starts again [Duchêne and Touya, 2010].

As a result, CollaGen allows the generalization of heterogeneous landscapes using several agent- and not agent-based processes [Touya and Duchêne, 2011]. Figure 12 shows a small town generalized by AGENT and the rural area around by CartACom while roads are generalized by the

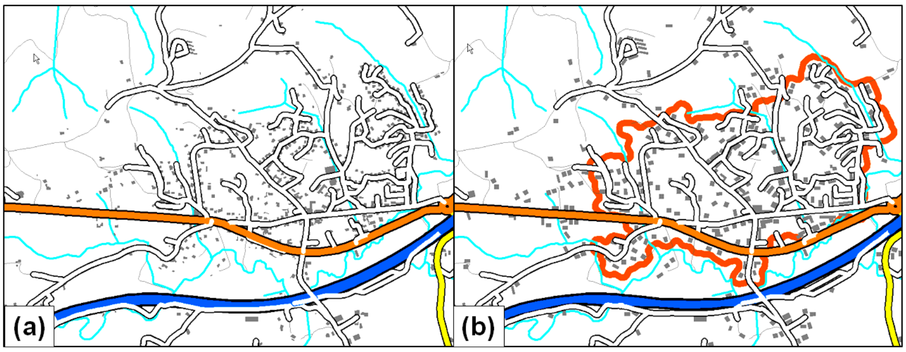

Figure 12: Initial data (a) and generalized data by CollaGen. (b) The urban area is delineated to show space agents.

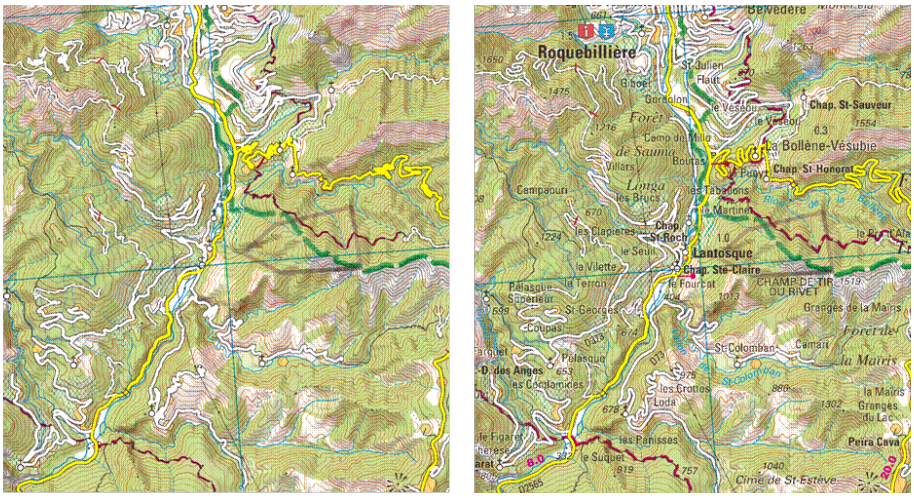

Figure 13: Derivation of the 1:100k topographic map (right) from the BD CARTO® database (left, 10m resolution) at IGN-France [Lecordix et al., 2005].

Elastic Beams [Bader et al., 2005].

4.6 Implemented software prototypes and use for actual map production

Some of the agent-based generalization models presented above have been industrialized and are used in production in European NMAs [Duchêne et al., 2014]. First, the AGENT model has been implemented in the GIS LAMPS2 from 1Spatial during the AGENT European project. It then has been re-engineered and forms the core of Clarity, the generalization software of 1Spatial. These software have been customized for use in production among others at IGN-France, the French NMA: the 1:100k map production line uses the AGENT engine for the generalization of mountainous roads ([Lecordix et al., 2005], see Figure 13), and the new 1:25k map production line, currently being finalized, uses the AGENT engine for the generalization of built up areas and the GAEL engine to ensure the consistency between hydrography and relief ([Lecordix et al., 2007], see Figure 14). The quality of the results obtained in production show the interest of the agent based approach for generalization.

Besides the use in production of our models, we are trying to go further in research by tackling on-demand generalization. We identified a need for a development environment on which we can completely reimplement our three agent based generalization models AGENT, CartACom and GAEL while merging their cores, and which would offer specific functionalities dedicated to research. To answer this need, we developed a new agent based research platform for generalization named CartAGen [Renard et al., 2010]. It is implemented as a plugin of GeOxygene, the open source research platform developed in java at the COGIT laboratory [Bucher et al., 2012]. Links to Clarity are kept to be able to encapsulate basic generalization algorithms and specific mechanisms relying on Clarity's topological engine.

Figure 14: Derivation of the 1:25k topographic map (right) from the BD TOPO® database (left, 1m resolution) at IGN-France.

4.7 Other Multi-Agents Generalization Models

IGN COGIT team was not the first and the only research team to use multi-agents systems to automate map generalization, and some other models have been cited in the past sections. This is not the purpose of this report to detail such research, but an exhaustive review can be found in [Duchêne, 2016].

5 Discussion - Feedback from experimentations

5.1 Pros and Cons of Multi-Agents Generalization Models

Using geo-agents is not the unique way to develop automatic generalization processes and it can be interesting to discuss the advantages and the drawbacks of such an approach compared to different approaches. The first advantage of the agent-based approach is that it really is component-based (each capacity of the agent can be seen as a component), which makes it quite tolerant to local failures (*i.e.* a problem with one building agent does not make the whole town agent fail in the AGENT model). However, the better the components (and the generalization algorithms) are, the better the result is. Added to that, the geo-agent approach depends on a complete distributed model: a small part of the generalization problem is handled by each agent and each agent holds a part of the solution. It makes a global good solution much easier to obtain. The agents also allow to model heterogeneous entities with common aspects and specialized ones which fits well with the generalization problem: a building and a road have common aspects but also quite different ones as a road is part of network contrary to buildings for instance. Thus, common behaviors can be implemented at the agent level while specialized ones can be implemented at the road or building agent level. Then, multi-themes generalizations are possible with the agent approach.

Besides, the dynamics of the agents help to deal with the step-by-step approach as it is possible to manage online modifications and to update the context of the agent before it makes its decision. The agents also allow to model geographic hierarchies as in AGENT. The agents allow to model emergent phenomena: during the step-by-step generalization, unpredicted conflicts may appear ('emerge') and the agent modeling helps to deal with such emerging phenomena without disturbing the whole generalization process. Finally, as a component based approach, the agents allow the integration of other approaches as in CollaGen. Global resolution models like the least squares [Harrie and Sarjakoski, 2002] can be integrated as the action of a meso agent of AGENT for instance.

However, the geo-agent based approach involves some drawbacks that may be related to either the approach itself or the implementation it requires. First, the distributed aspect of the approach involves a complexity in the parameterization process. Indeed, each constraint requires its own parameters as well as each kind of geo-agent and it may be difficult to relate the diffuse parameters to the global objectives of the generalization. Notably, the translation of map specifications into the constraints satisfactions has been identified as a hard task: [Taillandier and Gaffuri, 2010] propose to use generalized samples to help a user translating specifications into satisfaction methods. The procedural knowledge required to guide agent-based generalization is also very complex (see Section 4.4), and might be specific to certain scale gaps or datasets. Recent research showed some potential to replace this procedural knowledge by pruning heuristics [Taillandier and Gaffuri, 2012], which could make agent-based processes more generic. Moreover, the geo-agent approach is heavy to implement and may be too much complicated in particular generalization cases where simpler approaches lead to good results. For instance, road network selection problems have been correctly solved by several workflow processes and do not need a complex geo-agent implementation. Finally, the geo-agent approach has proved effective but not very efficient because of the computation time required by the trial/error system. Such an approach could not be used to provide on-the-fly generalization services. Nevertheless, the inefficiency is more related to the step-by-step system rather than the agents as [Jabeur et al., 2006] proposed an agent-based model for online and on-the-fly generalization.

5.2 Research Agenda on the use of Multi-Agents Systems for Generalization

- *How to generalize (very) large datasets?* The agent-based models presented in this report have mostly been tested on rather small datasets compared to the extent of a country. Research on how to process large datasets with high performance computing techniques emerge [Thiemann et al., 2013]. Research also exist to distribute the agents of a multi-agents system into several computer nodes [Rousset et al., 2016]. In the case of agent-based generalization, it particularly raises communication and coordination issues.

- *Multi-level interactions.* The presented models handle direct hierarchical interactions between agents, or interaction between agents of the same level in CartACom, but the generalization often requires interactions between agents at different levels that are more complex than direct hierarchy [Maudet et al., 2014].

- *Improve collective decision making.* When many agents are in play in a situation (following the vocabulary from [Ruas and Plazanet, 1996], it can be very complex to decide what is the best sequence of algorithm to trigger. Distributed decision making is one of the main fields in multi-agents research, and strategies such as coalitions [Jabeur et al., 2003], votes, or multiple criteria decision techniques should be explored to improve collective decision making.

- *A better integration of novel learning techniques?* As generalization has been performed for years by human cartographers, researchers tried to capture their knowledge with machine learning techniques [Weibel et al., 1995], [Kilpelainen, 2000], [Taillandier et al., 2008]. Machine learning research recently made breakthrough advances, and we believe that the use of such techniques should be revisited to better guide agent-based generalization.

- *Agent self-evaluation and map global evaluation.* The life-cycle of the geo-agents is based on self-evaluation and on meso/macro/global evaluations that assess if the map is more legible after the action of an agent. While research on self-evaluation of micro agents presented good results [Bard, 2004], [Stoter et al., 2009], the evaluation of meso agents generalization, and the global evaluation of the map [Touya, 2012] are still research issues to improve the efficiency of agent-based generalization.

5.3 Additional Remarks

The previous parts showed how much the agent based approach rely on multiple components like generalization algorithms or spatial analysis tools. To obtain good generalization results, the components have to be effective. For instance, if the algorithm to eliminate buildings in too dense areas does not eliminate enough buildings, as good as can be the remaining algorithms, the results should be poor. Added to that, the agent based approach is not completely adapted to optimally solve every problem raised by generalization. Mixing it with different approaches may be useful. Notably, [Touya et al., 2010] shows constraints are not always adapted. Simple condition-action rules [Harrie and Weibel, 2007] may solve some problems like systematic geometry collapse in a simpler way. Condition-action or workflow approaches [Petzold et al., 2006] may also be simpler ways to overcome the difficulties to choose the next entity to generalize in our agent based approach.

6 Conclusion

To conclude, feedbacks from experience multi-agent based generalization were presented in this paper. Our approach was described as well as the several models developed at IGN France. Good results are obtained with this modular and adaptive approach as it optimizes the use of the generalization algorithms. The main drawback is the complexity of the distributed parameterization. The integration of agent-based and other approaches seems a promising to overcome current problems of the generalization research community. We plan to use the open source platform CartAGen[1] as a medium to foster collaborations on agent-based map generalization.

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