

# Self-Organisation in Agent-Based Simulation

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**Abstract.** In this paper, we investigate mechanisms via which a group of autonomous agents can produce emergent phenomena in artificial systems. In this framework, emergence deals with the appearance of new properties within a system of interacting agents. More particularly, emergence is here studied from a self-organisation point of view, that is a dynamic appearance of “remarkable” structures of agents. This work proposes an intentional modelling of mechanisms needed to give birth to structures in a multiagent system and a model of such processes. These mechanisms bring appropriate computational powers of expression to the system; they can be summarised by a meta-function and a local mechanism. The article emphasises the necessity of an emergent level to represent emergent structures, intermediary between the multiagent system and agents, the system being then distributed through three levels of description. To validate self-organisation processes, an application of simulation in Geophysics, showing the emergence of earthquakes is also presented. The paper concludes with some comments and issues for future works.

**Keywords.** Multiagent modelling and architectures, multiagent aspects of artificial life, emergence, self-organisation.

## 1 Introduction

This article focuses on emergence of new structures in multiagent systems, so-called self-organisation. It introduces some key issues associated with the understanding and representation of mechanisms leading to self-organisation. Self-organisation deals with the appearance, in a specific context and in an active environment, of new properties, not previously identified, and from now on irreversible within a system of interacting entities.

In order to explore such mechanisms, the framework of our project is to model and simulate the behaviour of complex systems with an agent-based approach. According to the oxford dictionary, the complexity of a system involves two or more components which are (1) joined

in such a way that is difficult to separate them, and (2) closely connected. This duality determines two dimensions of complexity which lead to the same approach in computational modelling. The distinction in several components leads to study the components structure, as the connection leads to study the dynamic of interactions. So, a complex system is seen as a non-linear system, in which the result of interactions between its components exceeds their individual contributions. Complexity is a property found in many kinds of natural systems, in physics, biology, social sciences... It is at the crossroads of different approaches, system theory, artificial life, cybernetics, artificial intelligence... Due to our local context and scientific environment, we began to tackle complexity through the modelling of natural systems, such as those studied in geophysics, i.e. earthquakes, volcano eruptions...

In geophysics, the study of this kind of system has led to the concept of *Self-Organised Criticality* [1], to explain the “repeatability” of phenomena in nature, which could obviously be observed in scaling laws. Such systems are driven by highly non-linear behaviour, where a small external perturbation could generate a large-scale phenomenon at a critical state of the system, but without predicting when it could appear [12].

The important aspect of the behaviour is the apparent robustness of these scaling laws, the term criticality referring to the fact that there is no time scale in phenomena repetition, and the term self-organised to the fact that the critical state is an “attractor” for the system’s dynamics [2]. The best well-known example illustrating this property is the “repeatability” of avalanches in a sand pile, where grains are randomly added during experimentation. Such a system describes a degree of complexity more important than its parts, and includes properties which could not be reduced to those of its components. This non reduction is assigned to the presence of interactions which dynamically unify the components of the system, and from which a phenomenon appears by affecting a part of the system. In some cases (earthquakes or volcano eruptions for instances), the affected part of the system is forming some new remarkable structures, which then could force in his turn his components, and plays a causal role in the system for future behaviour (for instance, there is no eruption, nor earthquakes twice a time at the same place).

In natural phenomena modelling, the role of simulation is interesting, because simulation can adequately capture any behaviour likely to be observed, and is used to exhibit new structures and tackle their causal role in the system.

This paper deals with the intentional modelling of self-organisation mechanisms, leading to a dynamic re-organisation of the acquaintances network. We try to answer the question of how an artificial system, composed of simple agents interacting each other, could generate emergent structures. The appearance of emergent structures in a component C is seen as the consequence

of dynamic interactions (causal links) between components of fine grain components of  $C$ , involving a *scale change* and, by derivation, the presence of fine-grain and coarse-grain agents. In complex systems, fine-grain components are assumed to be determinist, as coarse-grain components are not, because their behaviour is not linear during time.

In the domain of complex systems modelling, emergence should be distinguished between evolution and adaptation. *Adaptation* rather refers to agents' behaviour which should be adapted because the environment is changed or moved, as a consequence of self-organisation. Adaptation is then defined as the capability of an organism to improve and adjust behaviour to his environment. Adaptation is pointed out as research perspectives of this work in the conclusion of the paper and is out of scope of this paper. *Evolution* dynamically produced results, and concerns:

- Knowledge evolution, as the result of autonomous agents' internal parameters computation.
- Agents' neighbourhood evolution or self-organisation. This property allows a system to be organised or re-organised during time, as far as the simulation processes. In complex systems modelling, self-organisation is a very interesting feature, and has been tackled in several domains. In cognitive sciences, the behaviour of a group of students is simulated during their daily route through a campus and a trail emerges by the system's dynamic [3], [6]. In socio-biology, the collective organisation of social insects is shown highly sophisticated, as individual organisation is limited and apparently random [18]. In geology and geophysics, self-organisation is intrinsic to self-organised critical systems. In sociology, some works aim at understanding emergence of organised societies, and explain transitions from small families to large groups and tribes, or explain relationships between institutions and individual phenomena such as beliefs [10].

The paper is divided into four main sections. Section 2 discusses of mechanisms to implement in multiagent systems in order to achieve self-organisation. Section 3 presents our architecture based on three description levels to represent emergent structures, and proposes an implementation of such mechanisms. Section 4 presents the experimentation which has been tackled to validate the architecture and the associated self-organisation mechanisms. Finally, section 5 summarises this work and concludes the article by pointing out current investigations and further research perspectives.

## 2 A Model of Self-Organisation Mechanisms

Emergent phenomena should not be confused with internal mechanisms which give birth to them. This section introduces the basis of self-organisation in multiagent systems, that is a set of mechanisms able to analyse conditions of a phenomenon appearance, and to observe it.

The first mechanism describes how a phenomenon emerges in a multiagent context. It concerns the description of the conditions which will trigger emergence, and the mechanisms needed to make the phenomenon visible. This mechanism is tackled in section 2.1 below. The second mechanism is intended to answer the question of how can we observe that self-organisation took place and watch the result. This “observer” should make emergent phenomena intrinsic to the system, and study the conditions under which the phenomenon stops. This mechanism is detailed in section 2.2.

### 2.1 Intentional modelling of emergence: artificial emergence

How a phenomenon could emerge governs the system adaptation capability, and depends on the state of the agent and the environment at the time the phenomenon occurs. To satisfy self-organisation, it is necessary to dispose of:

- mechanisms in charge of detecting the conditions which will trigger the phenomenon, and stopping the process when finished. These mechanisms act at a local level and are then defined as a part of the agent’s behaviour;
- a mechanism to give birth to the phenomenon, and in charge of its representation and visualisation through the system. This mechanism looks like a “*meta-function*”, which should evaluate pre-conditions given by the trigger, and manage the emergent structure. It acts at a global level and is then defined as a part of the agents’ society.

However, we claim that this kind of emergence should be understood as “simulated”, because the way how such structures occur is totally described by a determinist process (as results of such processes are not). In the area of complex systems, we argue that, because researchers do not actually have sufficient knowledge, it is not yet possible to formally explain the results. One of the consequences is that emergence can be perceived as “*built*”, and we believe that a real and strong emergence (so-called “*high emergence*” in the following by opposition to “*built emergence*”) is not an intrinsic characteristic of artificial systems. Emergent phenomena in artificial systems could be explained, but it is rather because actual human-knowledge is not sufficiently advanced to do so. High emergence is considered as a

characteristic of natural systems rather than artificial systems, a natural system defining an unclosed world, in which all situations are not known by the designer. In such systems, natural phenomena are highly emergent due to ignorance of governing laws.

We then agree with Mitchell and Hofstadter's dissertation in [17], who specify that explanations about emergence can only be done at a micro-level, because human-knowledge fails when trying to explain it at a macro-level. We refer hereafter as "*artificial emergence*" the emergence property in artificial systems, provided by a meta-function analysing both the environment and agents' current states. As we do not know how to explain it, artificial emergence is a very interesting feature to investigate which could help to implement it easily, and finding architectures and frameworks to make use of it is one of the primary objectives of this work.

## 2.2 The role of the observer

This mechanism is in charge of the observation of the self-organised phenomenon. This observation is essential in simulation, as it constitutes a natural interpretation of the results of the emergence. The observation must be *visible* from an external point of view, *designed*, and *programmed*. These considerations distinguish three kind of observers:

- An external human observer, for instance a end-user looking at the simulation results; for him, the results could be often surprising and seen as a kind of "magic phenomenon", as understanding the reasons for which structures emerge is indescribable and impossible to formalise [8]. This constitutes the external point of view of the emergent phenomenon, where the system surprises the user who only knows what occurs at the finest grain level. R. Brooks considers in that case, that emergence exists only when it is necessary to use new words to describe what is observed, and where these terms are not described in the fine grain level of the system [4].
- A designer observer, who knows what external observers are looking for, but does not know neither the exact result of the simulation, nor what will be exactly emerged from the simulation. So, for him, there is no magic phenomenon, as he controls the emergence capability of the artificial system. In addition, he describes internal actions of each agent to do so. For S. Forrest and J.H. Miller [9], if the result of interactions between agents leads to a non predictable effect for the designer himself, the emergence has to be qualified as high.
- A programmed observer, which is a part of the system, and is generally distributed among all agents. This observer gives the internal point of view of the system, this is the reason

why there is no magic part in the emergence process. Its role is to put in mechanisms detecting the end of emergence.

It is then very useful to dissociate such mechanisms, as it reduces the complexity of the design while preserving surprising effects for external observers. The next section presents the agent architecture we propose with that aim. It describes a specific level to easily integrate emergent structures in the system, as well as the implementation of self-organisation mechanisms used to reveal new structures.

### **3 Agent Architecture and Self-Organisation Mechanisms**

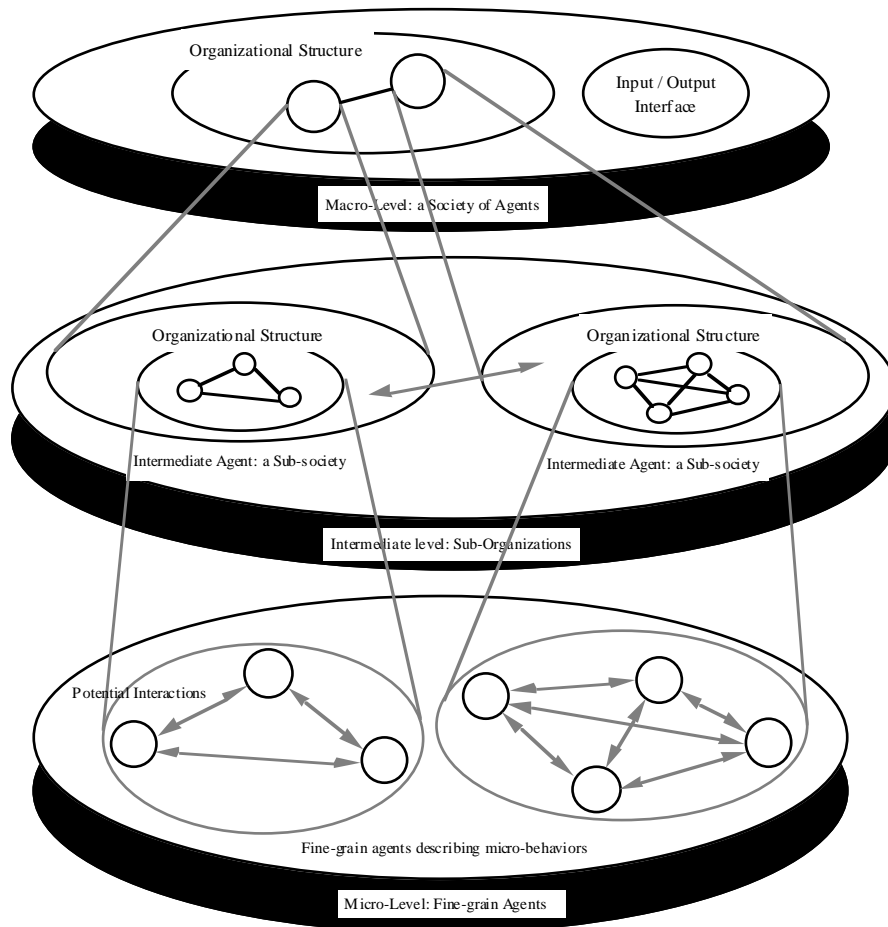
#### **3.1 Necessity of intermediate agents**

The purpose is here to characterise the emergence of structures in a complex system from local interactions between agents. In multiagent systems, two explicit levels are naturally described, a micro-level and a macro-level. The micro-level describes fine-grain agents with determinist behaviour, as the macro-level constitutes a coarse-grain agent representing the whole system, and organised as a society of agents. However, considering two explicit levels are not sufficient to give birth to new structures because:

- On the one hand, as a micro-level is described by fine-grain agents, the organisation of new structures can not be processed in such a microscopic level, which does not have enough knowledge to do so. Beyond this microscopic dimension, emergent structures can only arise in one macroscopic level, disposing of missing knowledge.
- On the other hand, it is often impossible for a macro-level to characterise and correctly identify the whole set of emergent structures. As a complex system is unpredictable and badly understood, trying to explain emergence mechanisms at the global level of the system fails. As a matter of fact, a significant number of micro-agents could intervene in the whole emergence process, making the system too complex to analyse at a macro-level.

It is then useful to introduce an intermediate grain level between the macro-level and the micro-level, embedded as sub-organisations of the society. Such an intermediate level is not predefined in the system and can spontaneously appear during the simulation as the result of self-organisation. It is dynamically built by a bottom-up approach. This point of view enforces the necessity of finding the most efficient abstraction when designing this level, which is totally dependent of the context tackled. When self-organisation arises, it gives birth to new

sub-organisation. The new structure itself describes a society of fine-grain agents which have given birth to it, and at the same time, is viewed as an agent of the society defined in the macro-level. The intermediate agent disposes of own properties, and makes the association between fine-grain agents in a new organisational structure. These agent's properties are set at the time the organisation is built. Such properties are then "re-introduced" in underlying lower-level agents as constraints to apply in their own structure. By this way, an intermediate agent is playing a causal role in the system, by constraining a part of it for the continuation of the simulation. Fig. 1 illustrates this intermediate level in the architecture.



**Fig. 1.** Agent architecture including an intermediate level

The three next sections present the self-organisation mechanisms. Section 3.2 describes the trigger mechanism which locally detects necessary conditions to initialise the whole process, section 3.3 discusses of the meta-function used to generate the new structure, and section 3.4

presents the programmed observer as the end-detection mechanism. Finally, section 3.5 briefly compares this approach with those of related works.

### 3.2 The trigger mechanism

The trigger mechanism is in charge of detecting conditions in the environment favourable to the appearance of emergent structures. Local interactions between fine-grain agents, at the origin of self-organisation, result in a modification of some internal properties which define the agent's state. The agent's state is assumed to be represented as a "state vector"  $P$ , from which each coordinate describes an internal property:

$$P = \begin{pmatrix} p_1 \\ p_2 \\ \vdots \\ p_n \end{pmatrix}, \text{ where } p_i \text{ correspond to the internal properties of the agent.}$$

In our system, the trigger mechanism is based on the detection of a *similarity* over state vectors, through agents of the same grain level. In our context, similarity is the most convenient way to detect common properties between two agents, but not the only one possible. For instance, complementarity or antagonism could be more adequate in artificial societies, and could open this issue to a larger extent. Similarity is based on the comparison of each agent's state with those of his neighbours. If an agent's state is recognised as similar with a neighbour's one, the two agents will be grouped together and embedded as a self-organised structure by the meta-function. The notion of similarity is here arbitrary and can not be formalised, as it could be interpreted with a margin of error and be totally dependent of the context tackled. In our system, it is quite simple, because the context tackled does not need to represent more complex activities in an agent, as in [5] for instance, where social relationships between two agents could determine an organisational commitment. To determine if two agents  $A_p$  and  $A_q$  are similar, it is only necessary and sufficient that:

- $A_p$  and  $A_q$  are neighbours,
- $A_p$ 's and  $A_q$ 's state vectors are respectively:

$$P = \begin{pmatrix} p_1 \\ p_2 \\ \vdots \\ p_n \end{pmatrix} \text{ and } Q = \begin{pmatrix} q_1 \\ q_2 \\ \vdots \\ q_n \end{pmatrix}$$

where  $\forall i \in \{1 \dots n\}, |p_i - q_i| < \epsilon_i$

$\epsilon_j$  defines a set of accuracy factors identifying the degree of similarity between the properties  $p_i$  and  $q_i$ . This parameter is accessible to the external observer, allowing the user with customising the application.

Two fine-grain agents which are mutually self-identified as similar are forming a class of similarity by self-organisation. A class of similarity then characterises some organisational structure linking agents with similar ones. A global mechanism is then needed because, when a similarity is detected, the trigger mechanism does not have enough knowledge on the global structure and can not then “aggregate” the agent at the right place. Such a mechanism is described by a meta-function, and is detailed now.

### **3.3 The meta-function**

The meta-function is locally triggered by a fine-grain agent when a similarity between two or more fine-grain agents has been detected by the previous local mechanism. The meta-function should be global and defined as a part of the behaviour of the society. This global mechanism is in charge to create an intermediate agent to aggregate similar fine-grain agents, or to add such agents to an existing one. If one of the two similar agents is already member of a sub-organisation, the meta-function advises the underlying agent managing the sub-organisation, which integrates the new fine-grain agent within the existing structure. Note that if the two micro-agents are members of two different sub-organisations, they can be integrated on both sub-organisations, to take different emergent phenomena into account. If no intermediate agent has been created to model the similarity class found: in such a case, the meta-function is creating a new intermediate agent responsible of the emergent structure. This agent will be populated step by step as similarity classes will be detected.

Finally, note that such an encapsulated fine-grain agent could leave the structure at any time, if his state evolves. If only one agent remains in the structure, the sub-organisation disappears. Beyond this mechanism, an intermediate agent can react as a feedback on each member of his structure, to introduce constraints which should be applied to all agents of the organisation. With that aim, the meta-function should compute appropriate values for the new agent’s properties. Setting new properties in an intermediate agent becomes easy at this point, mainly because the meta-function could pick up information from lower-level agents by the trigger mechanism. The, during next interactions, the emergent society could force the behaviour of underlying agents, by applying them some of these properties.

### **3.4 The programmed observer**

The role of this programmed observer is to look at the end of an emergent phenomenon, that is when local constraints are no more strong enough and the system in a stable state. The programmed observer is generally implemented as a global loop inserted over the multiagent system or as a part of the society, to inspect the stability of underlying agents forming the structure. In our architecture, the programmed observer is locally defined, and is supplementary to the trigger mechanism. It acts as a end-detection mechanism, embedded in fine-grain agents, and examines the neighbourhood to look at potential agents not enough stable and able to propagate again the phenomenon. The end-detection mechanism consists in computing the number of these fine-grain agents remaining unstable. Thus, when the counter becomes nil, the end of propagation is detected.

### **3.5 Conclusion and comparison with other approaches**

The whole self-organisation process of our model acts both at a local and global level. The method used to initialise the emergence of structures is based on the detection of the similarity which was guided by the context tackled, that is natural phenomena modelling in geophysics. At this step, the model seems too restrictive to be used in a more general context. However, we think that this self-organisation model allows (1) to represent emergent structures in the system, and (2) the system with integrating them in the system, taking account of new constraints which could appear as the result of the emergence.

In the MANTA system [7] which simulates the socio-genesis of an ants colony, different entities involved in the colony's life are modelled by reactive agents at a micro-level. The adaptive performance of the society results in the basic behaviour of its members. In the MANTA system, the generation of social patterns in the ants' society could be observed, but any explicit structure is defined to organise them.

In the SWARM system [16], an agent can also itself be a swarm: a collection of objects and a schedule of actions. In this case, the agent's behaviour is defined by the emergent phenomena of the agents inside its swarm. However a swarm do not explicitly dispose of any organisational structure.

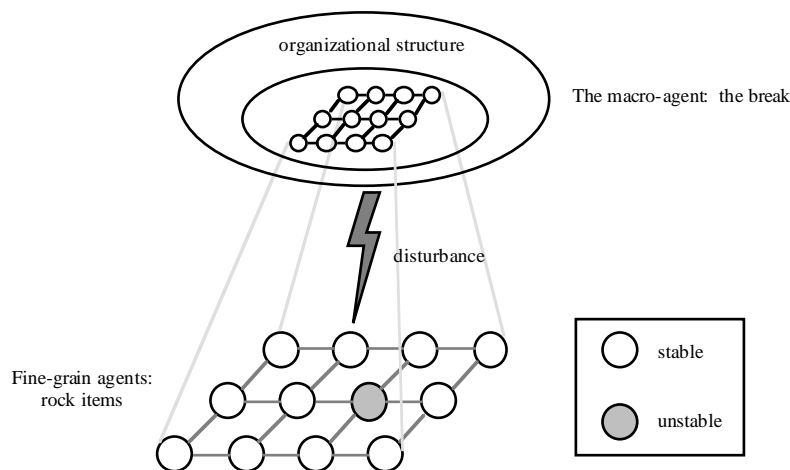
Lastly, cellular automata constitute parallel computation models, which allow to create virtual worlds represented by matrix, and synchronously evolve with the help of sample local rules. Emergent structures could be observed, they form topologic structures within the matrix, but are too sample to get new properties. Therefore, they can not be as semantically richer as multiagent systems, because behaviour of emergent structures are not driven by properties derived from the self-organisation process.

The next section presents an example of such mechanisms in the context of a natural phenomena simulation applied to earthquakes modelling.

## 4 Self-Organisation Experimentation

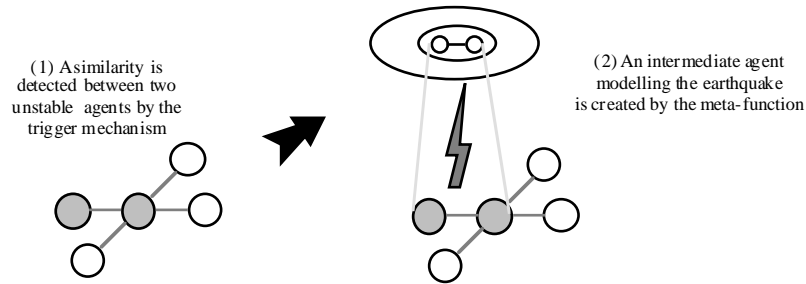
The application we propose to model is dealing with a geophysics system representing a “break”, composed of rock items, and subject to earth’s crust constraints. Each rock item is characterised by rheologic properties which constitute internal data, represented as a state vector. Micro-behaviour is defined to react to disturbances of the environment by fitting the state vector. When a fine-grain agent becomes unstable due to disturbance, he releases some energy and, if the amount of energy is sufficient, propagates the disturbance to the neighbourhood. This propagation could lead to an earthquake in the break, which will be represented by an emergent structure in the system. In such a context, self-organisation is seen as the appearance of earthquakes in the system. We are conscious of the simplicity of the experimentation; however, we think that it is a good place, as a first step, to test the mechanisms previously presented, and show how a non initially constrained system could be organised as events arrive. This is specially useful in the frame of natural phenomena such in earthquakes prediction, as researchers are attentive at spontaneous emergence of order in a system which looks like randomly initialised [13].

At the beginning of the simulation, the multiagent system is represented in a macro-level modelling a break, and a micro-level modelling rock items. Fine-grain agents representing rock items are defined with a state vector randomly initialised which determines their stability:



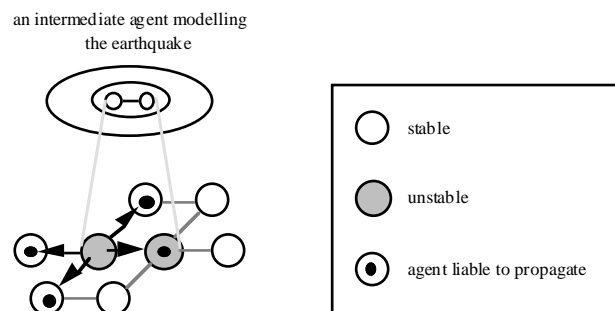
**Fig. 2.** Modelling a break in the architecture

The disturbance is initially distributed among rock items and is asynchronously interpreted by each fine-grain agent, which reacts by setting his state vector and releases energy to each neighbour, causing a disturbance in series. The local trigger mechanism is then set each time an interaction occurs, and detects similarities between unstable fine-grain agents. Such similar agents will progressively generate the earthquake, and will be “aggregated” as an intermediate agent by the meta-function:



**Fig. 3.** Creating intermediate agents in the system after similarity-detection

The end-detection mechanism, embedded in the intermediate grain level agent, examines the potential number of rock items which remain unstable and can still propagate the phenomenon (marked with a black point in Fig. 4 below):

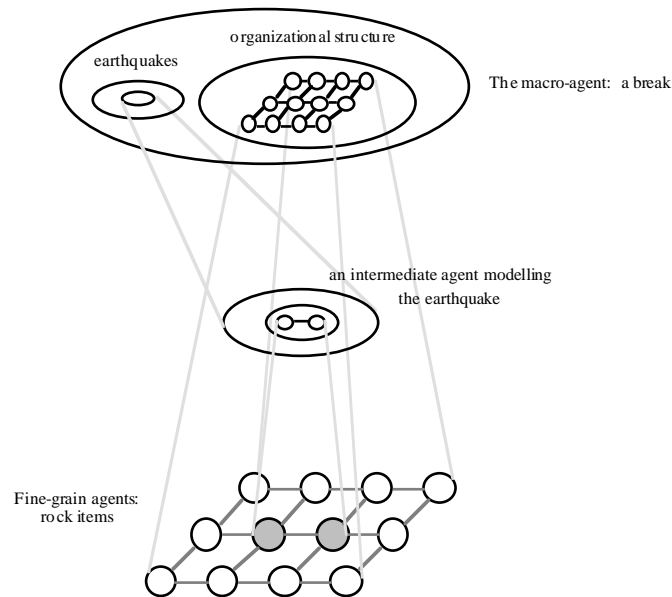


**Fig. 4.** The programmed observer as the end-detection mechanism

Finally, after all fine-grain agents are stabilised, no more agent is enough constrained to participate at the earthquake, and the generated structure is completely defined and integrated in the system, as shown in Fig. 5 on next page.

Note that the new structure is now bearing new properties, such as earthquake size and magnitude for instance, which have been computed by the meta-function when creating the earthquake. This is important to take into account, as such a disturbed system can not behave

as before earthquakes appear. So, these properties will then be distributed again on each agent making up the earthquake, as far as the simulation processes.



**Fig. 5.** Giving birth to earthquakes

The recursion property of multiagent systems is here preserved: the emerging structure of the earthquake is now on irreversible, and is considered both as an agent of the society in the macro-level, and as a sub-society of agents in the intermediate level, composed of old unstable fine-grain components which have given birth to it.

This application has been implemented with the help of ReActalk [11], an open environment to develop and experiment with agents. A graphical interface has been realised in smalltalk-80 to set simulation parameters, and to follow the phenomenon during the simulation, as earthquakes appear. Our agent-based approach has been validated on the Miller's model [15] of a break, subjected to earth's crust constraints. From local basic behaviours, the model we implement has reproduced the break complexity at a global scale. The adequation between synthetic data and in-situ observations of such a break helps in validating both the architecture and the associated self-organisation processes. Further experimentation have been led to simulate a model of a fluid's tank (in a porous environment), encapsulated in a matrix of rocks (most of the time not porous) and the same kind of results have been reported.

## **5 Concluding Remarks**

This paper has discussed of underlying mechanisms of self-organisation in artificial systems. We argue that emergence in artificial systems is “built” rather than “high”, mainly because the way how a phenomenon emerges is always given by the designer. However, according to the emergence paradigms and points of view, this kind of phenomenon has to be considered as emergent.

Emergence has been studied from a self-organisation point of view in multiagent systems intended to model complex systems. We have pointed out how the study of emergence properties leads us to derive appropriate computational mechanisms. Several needed mechanisms have been identified, such as a trigger, a meta-function, and an observer.

Though systems validated in this context are quite small, during simulations, agents are faced much of time to the same kind of conditions. The repetition of the same actions leads the system to become less powerful. To address this issue, the system has to analyse the conditions which drive the best actions. It is then necessary that multiagent systems should be equipped with the ability to learn, that is, to automatically improve their future performance. Machine-learning techniques are good candidates for making the system more intelligent and better drive the emergence process. Thanks to the observation of similar situations, such techniques could generate rules allowing an agent with choosing the most adapted behaviour to perform. By derivation, if such rules have been learned by a macro-agent, some inputs events can also be intercepted, and locally performed by this mechanism. Primary tests with these techniques were first introduced in our architecture to look for the convergence of certainty factors when agents broadcast messages everywhere in the network [14]. Our platform is actually re-engineering with the aim of keeping researchers close to such goals.

## **Acknowledgements**

We are grateful to those people that read and commented on earlier drafts of this article, and those people who have brought their contribution to this work, C. Bergeron, S. Giroux, J.R. Grasso, D. Grosser, J. Quinqueton, and all members of the AFCET-IAD working group, for their encouragement, enthusiasm and helpful feedback.

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