

# Self-organization of multi-agent systems

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**Abstract.** When one has to design multi-agent systems for realistic world applications one needs a certain level of self-organization to be able to cope with the dynamic environment. The self-organization can manifest itself in different aspects. It depends on the application on which aspect one should focus the research effort. We have identified which aspects we consider important, and translated this into research questions to be addressed in running and upcoming national and international projects.

## Introduction

The new trend in Artificial Intelligence is to investigate the effect of situated interaction in realistic worlds. For example, a swarm of robots gives the possibility to embody intelligent systems, and situate them in an actual environment [1]. This makes it possible to find the relation between actions and observations in a realistic situation, and to experiment with the interaction, communication and coordination between the multiple embodied agents.

Most recent applications of agent-based systems are so-called closed agent systems, in which agents interact with each other by means of structured and predictable communication protocols. All actors within the system are known in advance, including their characteristics, and all conversations follow predefined patterns. We like to focus on open agent systems: agent organizations that are dynamic, adaptive and can cope with unstructured and complex open environment. In an open environment an agent organization will need to be able to adapt to environmental changes: agents may join or leave the organization, new information sources may become available or communication lines may change.

To be able to function as an organization, the members of that organization not only need a (primitive) understanding of the situation they are confronted with, but also have to realize that there are other entities inside the organization, and what their relations to those other entities are. To build this sort of relationships, a basic set of mechanisms is needed to enable the formation of a team from a group of agents.

## Self-organization of multi-agent systems

Most man-made technological systems rely on an intelligent operator. The whole system is controlled by an operator in a centralized manner. This has led to the misconception that automated control is the best practice to automate the operator. If we want to design robust intelligent systems this might not be the best architecture. Centralization comes at a price. By introducing a functional hierarchy, various components will unnecessarily become crucial to the system. If any of these components fail, the whole system will be out of order. Many natural systems are structured by their own internal processes, because components are dynamically added or removed from the system. These systems are self-organized. The way in which behavioral and structural patterns emerge is a complex phenomenon that intrigues scientists from all disciplines.

A classic example of self-organization for the AI-community is the colony behavior in social insects, with semi-intelligent workers accomplishing complex tasks without explicit steering (see for instance the experiments described in [2]). With that analogy in mind we define a self-organizing system with the following set of definitions:

- A system can be defined as a group of interacting agents that is functioning as a whole and distinguishable from its surroundings by its behavior.
- An organization is an arrangement of selected parts so as to promote a specific function.
- Self-organization is the evolution of a system into an organized form *in the absence of an external supervisor*.

The property of self-organization makes it possible to build systems with unique characteristics. To emphasize the differences between a conventional system and a self-organizing system we take the example of a mechanical clockwork as a conventional system. For its functioning the clockwork depends on the successful working of all its subparts and a clever design. Consequentially the failure of one cog will lead to collapse of the whole system. The robustness of the system can be enhanced by adding redundancy to its parts, but on the end this is a waste of resources. It would be preferable to add generic components to the system together with self-organizing capabilities [3]. Research in self-organizing multi-agents systems can make it possible to:

- Design and build systems that are *fault-tolerant*, i.e. systems that maintain their functional integrity despite partial (unit) failures.
- Simplifying system maintenance by extending them with some degree of "plug and play functionality", i.e. allow self-installing and *self-configuring* components.
- Enable *high level control* of systems, i.e. instead of controlling the behavior of each individual system part we will rather control the system at subsystem or system level.
- Extend the system functional scope by enabling some degree of *adaptation*, i.e. have a system autonomously optimize it's functionality given its beliefs of the current (or even expected) situation.
- Enable large collections of independent hardware/software components to coordinate their behaviors and strive for an implicit defined collective goal.

The benefits of these characteristics can only be shown in a context of an application area, so we need multiple projects to show the added value of self-organization.

## **Agent organization aspects**

The aim of this research is to study the principles of self-organizing teams of intelligent agents deployed in the real world. So these agents have the capability to sense, reason and act. Multiple aspects play a role in creating self-organizing behavior from such system. A system's architect has to choose how each aspect is dealt with within the system.

In the research of the coming years we want explore how different values for these aspects affect the overall behavior, and how well certain solutions fit in different application areas. We distinguish the following aspects of interest:

### **Aspect 1: Common Goal**

Agents in a multi-agent system can collaborate or operate solo. A premise for collaboration is the existence of some benefit in working together. Collaboration can take the form of work-sharing (lifting heavy loads, exploring large areas) or task division (some agents facilitate the specialists in the team).

It is not trivial to create good metrics to estimate how the actions of the different members of the team contribute to reach the common goal, and to reward them in a proper sense, to facilitate learning.

The opposite from collaboration is when each agent has its own individual goal, and gets engaged in a collaborative action only when that suits its selfish needs.

### **Aspect 2: Agent Diversity**

Homogeneous teams are well suited for teamwork since it is relatively trivial for an agent in a homogeneous system to “model” its fellow teammates. Still, absolute knowledge about the behavior of its teammates is not possible as long as the communication lines are not perfect, because two ‘similar’ agents on a different location will not have the same situation awareness. Heterogeneous teams have natural ways of labor division. Some tasks have to be performed by a certain member of an organization, because it is the only agent capable of performing this task. Also weaker forms of heterogeneity are possible, when not all agents are *interested* in performing a certain task. [5]

### **Aspect 3: Team Formation**

Fixed teams (teams with a persistent configuration) can improve their performance by optimizing their behavior as team, learning to predict each other’s behavior in many circumstances, and in this way are able to accomplish critical tasks with a limited set of resources.

On the other hand, organizations can keep functioning while the composition of their organization keeps changing (till a certain limit). The number of team members can for instance decrease or increase. Important are the capabilities of the team members that leave or join the organization. Dependent on these capabilities, it can be necessary to reorganize the team, and distribute the different roles in the organization in a new way.

Dynamic teams will probably yield a greater flexibility at the expense of efficiency for standard tasks.

### **Aspect 4: Coordination**

Even when all members of an organization are operating towards a common goal, it is possible that the world model of each agent is too limited. In that case it can happen that opportunities are missed which a central coordination unit could have found. From the other side, the central unit is a single point of failure, and distributed the decision power to the field has its benefits.

### **Aspect 5: Communication**

Under the constraint of limited communication bandwidth, the amount of communication can be reduced when adequate peer modeling is employed. In that case an agent will reason about the expected behavior of its peer agent. The extent to which modeling is a sufficient substitute for communication, and the subset of peers that has to be modeled in order to be able to operate efficiently and effectively are still open questions. See for example [5].

## Research Questions

In the context of the DECIS Lab<sup>1</sup> we participate both in the ICIS and COMBINED systems program, and participated in the RoboCup Rescue competition. Part of the research concentrated on situation awareness, which can be defined [6] as

- Situation awareness is the perception of the elements in the environment within a volume of time and space; the comprehension of their meaning, and the projection of their status in the near future.

The environment can be observed by so called Distributed Perception Networks, an agent-based approach to fuse heterogeneous data [7]. Each Perception Network has a Causal Model and a Reasoning Engine. With respect to the Causal Model, observations can be traced back to hidden causes, and predictions can be made on the probability of a world state, which can be used for decision making. This work can most naturally be illustrated with a **Remote monitoring** application.

Another part of the research concentrated on communication and coordination aspects, which can be illustrated with a **Crisis Management** application. For both applications we will discuss how the five following research questions can be addressed. These research questions are closely related with previous introduced aspects.

1. What are the appropriate metrics to estimate the contribution of individual actions to a common goal?
2. How do we distribute the tasks over a team when the agents have overlapping, but not complete heterogeneous, capabilities?
3. How can we find the balance between flexibility and performance for teams that have nearly fixed composition?
4. How much of the local world models have to be known by a central coordination unit to be able to steer the overall behavior?
5. To what extent is peer-modeling a sufficient substitute for communication?

### Remote monitoring

We envision that monitoring an area requires long lasting employment of a large group of embodied agents. The responsibility of fulfilling the system's task is shared amongst the members of this group. Typically monitoring movements (e.g. of troops, smugglers, oil) requires multiple agents to share information. If actions are to be taken, multiple agents will be involved. Take the example of an oil leakage. Some agents detect the oil and monitor its movements. Others will try building a flexible dam at an appropriate location, while a third group gets ready to clean up the oil near the dam. Local actions should be simple to guarantee availability over long periods.

In our research performed in the COMBINED project [7], the focus was directed on the observation part. Distributed Perception Networks were designed, which support robust and efficient situation assessment. Based on an information request, a distributed Bayesian Network is formed, that makes it possible to combine the information in local Bayesian Networks in a meaningful way. This unique distributed fusion approach has several benefits, which we will highlight on the basis of the research questions.

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<sup>1</sup> <http://www.decis.nl/>

**1. What are the appropriate metrics to estimate the contribution of individual actions to a common goal?**

Currently the information provided by the Distributed Perception Network is not directly related to actions, it only provides reliable information for decision making. Yet, one can monitor the contribution of the different distributed Networks in the fusion process at higher levels. The information maintained in a local Bayesian Network can also be used for actions possible by that agent.

**2. How do we distribute the tasks over a team when the agents have overlapping, but not complete heterogeneous, capabilities?**

Only Perception Networks with the right sensors in the right area respond to an information request. Problems arise when neighboring Perception Networks have overlapping special areas. Conflicts can then occur over the active control of a certain sensory resource. This conflict can be solved by optimizing the global fusion process, but currently an algorithm is evaluated that resolves the conflict by bilateral exchanging of their measures of uncertainty.

**3. How can we find the balance between flexibility and performance for teams that have nearly fixed composition?**

The concept behind the Distributed Perception Networks can be summarized with the view that there are many sleeping Fusion Agents, which only become active after an explicit request for specific knowledge about a certain area. The sensors in the local network are already present, but are outputs are fused in case of an emergency. The majority of these sensor suites will be based on measuring simple features as sound or movement. However, specific monitoring applications may require specific sensors – insight is required in the proper balance in the distribution of those sensor resources.

**4. How much of the local world models have to be known by a central coordination unit to be able to steer the overall behavior?**

The Distributed Perception Network approach was designed with the explicit requirement that there is neither central control nor a global world model. At the moment that an agent has a question about the state of the world that cannot be answered by the local Perception Network, it initiates dynamically its own Distributed Perception Network by connecting to other Perception Networks that can contribute to reduce the uncertainty about that question. The information provided by the other Perception Networks is the result of the internal reasoning process. Each Perception Network maintains its own partial world. The domain knowledge is completely distributed

**5. To what extent is peer-modeling a sufficient substitute for communication?**

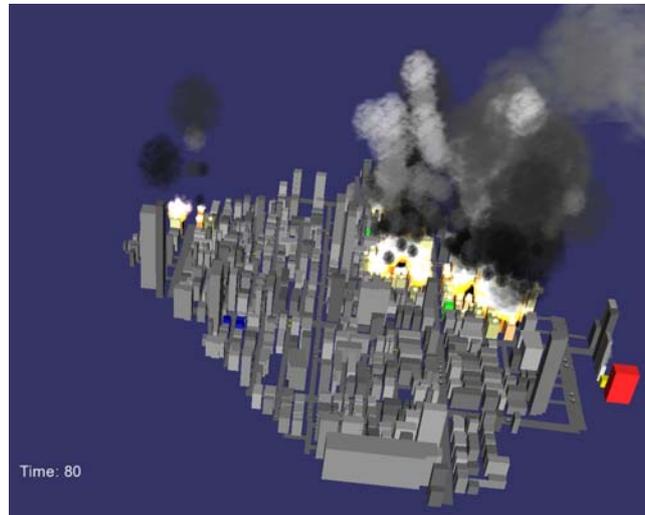
The Distributed Perception Network approach is based on the producer-consumer paradigm. New fusion networks can be dynamically built by requesting agents that can provide certain services. This knowledge about peer-networks can be memorized locally, but for flexibility reasons the latest information is requested every time a new fusion network is built.

The amount of communication in the initialization process is minimal compared the information flow during the fusion process. Yet, the information flow is localized between nearby nodes, the Distributed Perception Network approach requires no information flow over long distances as in the case of centralized approaches.

The experiments performed with Distributed Perception Networks show that this sort of systems can provide reliable information about the world, including confidence estimates. Further the systems can be easily extended, which allow the construction of large sensor networks .

## Crisis management

Crisis management can benefit from using artificial agents to take over human roles in a chaotic situation after a major incident. Rescue robots can play a role when it is too dangerous for humans to enter the scene. Robots will be deployed as part of specialized, static teams. Teams of intelligent agents can also play a role in situation assessment and organization of the rescue operations [8]. Flexibility is an issue, since this is a requirement for the humans as well. How can agents have the same flexibility of humans having similar roles?



**Fig. 1.** Burning city after an earth-quake, 3D visualization for the Robocup Rescue Simulation Project [9]

To evaluate the possibilities of multi-agents systems in this sort of scenarios, the Rescue League was introduced at the RoboCup initiative [10]. In the Real Robot competition the interface to humans is very important, in the Simulation competition the focus is mainly on the communication and coordination aspects. With our contribution in the Simulation League [11] the research questions were addressed in the following way:

### **1. What are the appropriate metrics to estimate the contribution of individual actions to a common goal?**

In the Simulation League a team of rescue agents have to make the right decisions so save a city and its inhabitants after a major earth quake. The contributions of the different competitors are compared on an overall score. The natural metrics to steer the behavior of a single agent is to estimate the effects of its actions on the overall score. The difficulty is that some actions can take a relative long time to accomplish (as for instance extinguishing a large building), while in the mean time the situation and the awareness of that situation is changing. For instance, the spreading of fires after the earth quake are difficult to predict, and starting fires can only be observed from close range. Some universities [12,13] have designed algorithms based reinforcement learning to associate the situation to the right action. These learning algorithms should in principle be able to predict the long term effects of an action, but are mainly used to find priorities between the possible actions at that moment.

In our research we have experimented with a game-tree approach. In this approach the agents construct a strategy for multiple future cycles instead of just selecting the behavior which currently has the highest priority. They do that not only for themselves, but also for a limited number of team members. This game-tree approach can also be used to trace the situation and the behaviors of the agents multiple cycles back in history, to estimate which actions were really beneficial on the long run.

## **2. How do we distribute the tasks over a team when the agents have overlapping, but not complete heterogeneous, capabilities?**

In a crisis situation cooperation is essential. The different rescue agents in the Simulation league all have their own special capabilities and one overlapping capability. All rescue agents can be used for reconnaissance. It is important that the team maintains a good overview of the general disaster level, to have an indication of the number of burning and collapsed buildings around the working area. For the 2005 competition it is proposed to introduce a "capability based" system. Instead of having "fire agents" and "police agents", for example, each agent would have a set of slightly different capabilities.

What remains important is that police agents have a supporting task: they have to clear the roads for the ambulances and fire brigades. This is ultimately a pro-active task, the road to the next location can best be cleared while the ambulances and fire brigades are still busy. This means that there has to be a coupling between the planning of the police agents and the other rescue agents.

## **3. How can we find the balance between flexibility and performance for teams that have nearly fixed composition?**

Initially only the local rescue forces are present in the city. After the disaster it is critical to bring the organization to a size that matches the disaster, without disturbing the initial emergency activities [8]. This scaling-up process is a nice topic for MAS research, however the current Simulation League cannot model the arrival of other agents at the incident. We like to propose this feature in future competitions.

What is already important in the current models is the formation of teams that concentrate their effort in a certain sector [11]. This is a dynamic process, multiple times performed during a simulation run. Currently the agents decide for themselves to which team they belong, but we like to research the impact of a central coordination unit.

## **4. How much of the local world models have to be known by a central coordination unit to be able to steer the overall behavior?**

At present we have experimented with a central coordination unit that only redistributes the world model. In this approach just observations are distributed, the communication channels are not used for negotiations, request or orders of certain actions. We are thinking to use the communication channels to exchange partial game-trees, but also here the central coordination unit only serves as distribution centre. The central coordination unit can serve a role at a strategic level, by assigning agents to teams in a certain region. For this decision the central coordination unit needs aggregates of knowledge about those regions.

## **5. To what extent is peer-modeling a sufficient substitute for communication?**

After an earth quake the communication infrastructure is likely damaged, and seen as a limited resource. Many messages can be sent, but only a limited number can be received. A communication scheme can be designed that guarantees the arrival of messages, by sending messages in phases. This means that the information exchange is not instantaneous, but takes typically four steps. Peer-modeling helps to estimate the situation a few steps ahead, until new observations arrive.

## Concluding remarks

Self-organization in multi agent systems is to be applied when it gives added value. The organizational structure within a multi-agent system can be explicitly designed, but is preferably an emergent property. This simplifies the design of systems that can cope with unforeseen events. The adaptive nature of a self-organizing system will continuously drive the system state towards the optimal solution.

Concepts of self-organization offer candidate solutions for very scalable designs. Individual parts may be added or retracted from the organization in a plug and play like fashion. Usually self-organizing systems do not depend on a single individual part and therefore robustness and fault-tolerance are inherent properties of these systems. This does not only hardware related fault-tolerance, but also tolerance in respect to uncertain and incomplete information.

Although the overall organization can be very complex, many self-organizing systems have relatively simple local components that are not "aware" of the macro-level organization they are contributing to. Last, but not least we expect self-organizing concepts to enable significant cost-reductions. These can be achieved because of less design and implementation efforts (simple hard- and software components), automation (less human-interfaces) and new control strategies.

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