A Self-organization Model for MAS Based on Trust

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Abstract. This paper focuses on addressing the challenge of maintaining information coherence and robustness within a multi-agent system (MAS) that aggregates information from distributed sources, some of which may be defective intentionally or unintentionally. We propose a self-organizational approach in this context, emphasizing a systemic perspective that considers structural coupling across two levels: direct information gathering and communication. Specifically, we integrate a trust mechanism with local behavioral rules and selective environmental pressures to facilitate the emergence of two co-evolving organizations: one at the social level and the other at the spatial level. The social organization mirrors the trust relationships developed among the agents, while the spatial organization represents the deployment of agents in the environment to encourage exploration. The local behavioral rules encompass three categories: deployment rules, communication rules, and retro-action rules governing communication and deployment. We conduct simulations to experiment with the combination of these behavioral rules, observing the emergence of organizational structures and roles within the system.

Keywords: Multi-Agent System · Self-organizing · Trust · Coherence · Robustness · TrustNet · Mapping

1 Introduction

Self-organization is the inherent capacity to shift from disorder to order or to transition from suboptimal organization to an improved one [2]. When applied to information systems, self-organization signifies the system's ability to enact changes autonomously, devoid of explicit external control. The organization naturally manifests through interactions and coordination among the system's components, guided by localized rules within the system.

Illustratively, envision a swarm of potentially flawed mobile robots collaboratively mapping a hazardous terrain. These robots accumulate information from their shared environment and exchange data with other agents. Perception and communication operate within defined range limits. Conceptually, the system can be depicted as a multiagent system (MAS) wherein each agent, representing a robot, strives to construct the most precise representation of its environment by collecting information directly (e.g., through its own sensors) and indirectly (e.g., via communication with other agents). Given the

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presence of defective agents, misinformation or inaccuracies regarding the environment can disrupt the system. In such a system, a significant question arises: how can we uphold the robust coherence of a multi-agent system without external control?

This paper introduces a self-organizational approach, rooted in a systemic perspective that acknowledges structural coupling between two vital components of the overall system: the direct information gathering component and the communication component. More precisely, we integrate a trust mechanism, amalgamated with local behavioral rules and environment-specific pressures, to drive the emergence of two co-evolving organizations. One operates at the social level, reflecting the trust relationships developed among the various agents. The other operates at the spatial level, mirroring the deployment of agents in the environment to stimulate exploration. The local behavioral rules encompass three categories: rules of deployment, rules of communication, and rules of retro-action, governing communication and deployment. We experiment with combining these behavioral rules in simulations to observe the emergence of organizational structures and roles within the system.

The paper is structured as follows: Sect. 2 provides an overview and contextualizes the general problem. Section 3 introduces a fundamental trust model pivotal to our self-organization model. Section 4 elaborates on our proposed model in detail. In Sect. 5, we present our experiments combining local rules to observe the emergence of self-organization and roles within the system. Finally, Sect. 6 offers a succinct conclusion and discusses potential avenues for future research.

2 General Problem Overview and Positioning

2.1 Problem Overview

The addressed issue deals with "how to maintain in a robust manner the coherence of a multi-agent system where some agents may be faulty?" It finally lands several underlying issues, namely:

– At the level of direct information collection, how to set up a mechanism which enables agents to optimize the exploration of their environment?
– At the level of communication, how to set up a mechanism which enables agents to better communicate when sharing the information about their environment?
– At the retroaction of exploration/communication, how to take into account the impact of the communication strategy on the exploration of agents in the system, and vice versa?

We propose to address these issues through a general conceptual framework in which we define local rules through a trust based mechanism. Rules are defined on respectively three levels: direct information collection level, communication level, and interaction level between these planes. By following these local rules, agents can behave to reach their goal without any outside explicit control. This also leads to the emergence of self-organization and roles in the system.

2.2 Our System Visions

Our approach is defined by the following core visions:

- A systemic perspective: The design of the entire system is envisioned to account for the interdependencies among key components, specifically the Direct Information Collecting System, Communication System, and their interactions.
- A self-organization vision: This pertains to an inherent control mechanism within the system. The system is tailored to emphasize internal mechanisms and dynamics that guide its organization, avoiding external imposition.

To operationalize these visions, we define constraints, establish local behavioral rules, and carefully balance positive and negative retroactions within our approach.

2.3 Related Works

Gleizes and colleagues [3, 6, 8] introduced a theoretical and practical approach for designing adaptive artificial software in dynamic environments. This approach is grounded in the AMAS theory and the ADELFE methodology, focusing on self-organization. However, it does not evaluate the system's overall function. The foundation of this approach lies in the AMAS theorem and ADELFE methodology, stating that for any functionally adequate system in a given environment, there exists a system with a cooperative internal medium that achieves an equivalent function. This evolving method is particularly useful when dealing with unforeseeable events in the environment.

Gershenson[7] proposed a methodology to assist engineers in designing and controlling complex systems, emphasizing the description of systems as self-organizing. Holzer et al. [9] described mathematical modeling of discrete complex systems and provided a framework for analyzing autonomy and emergence properties. Josang [10] presented an overview of attack types against trust and reputation systems, addressing research challenges in developing robust principles and mechanisms for trust and reputation systems.

Wolf and Holvoet [4, 5] proposed a comprehensive lifecycle methodology based on an industry-ready software engineering process, specifically tailored to engineer macroscopic behavior in self-organizing emergent MASs. Ye et al.'s work [14] introduced a decentralized self-organization mechanism in an agent network aimed at efficient task allocation through dynamic alterations of structural relations among agents.

Abdallah and colleagues [1, 15] developed a distributed, negotiation-based approach to dynamically form hierarchically organizational control, effectively coordinating DRL to enhance speed, quality, and convergence likelihood. Simonin and Ferber [13] presented a situated multi-agent model capable of addressing problems involving a range of agents from a few to hundreds. This approach extends the Artificial Potential Field technique. Klein and Tichy [11] proposed an approach relying on emergent fault-tolerance, where the desired behavior results from local reconfigurations of self-organizing agents.

3 Background: Trust System

In the recent years, trust and reputation became crucial issues in studying agent-based distributed autonomous systems in which software agents are faced with the uncertain behaviours of unreliable partners and need to select the most trustworthy ones to interact with. In such systems, trust among agents is one of the most important bases on which agents decide to interact with other ones. Trust is considered to be a belief that an agent has with a counterpart on honesty, reliability or reciprocativeness for some goal. Without trust, agents cannot efficiently cooperate.

Many current computational trust models are based on two factors: direct trust (linked to personal experience) and indirect trust (acquired from other agents). Our self-organization model is mainly based on a trust of this kind. In particular, we work on the trust model of Nguyen et al. [12]. We denote that:

- T_{ij} is the trust of agent i on agent j, including direct and indirect trust of i on j. The direct trust of i on j is based on the direct cooperation between i and j in the past. The indirect trust of i on j is estimated from the trust of any agent k which has cooperated with j and then shared its trust data with i.
- T_{ii} is the trust of agent i on itself.
- Each agent stores its own trust on other agents in special structures called TrustSets. When an agent j wants to cooperate with another agent k, j can estimate its trust toward k directly or indirectly, or both ways, using its TrustSet.

4 Self-organization Model

We examine a decentralized information collection system structured as a Multi-Agent System (MAS). Each agent within this system possesses the capability to explore, amass information items, and engage in communication. Information is acquired directly or indirectly through interactions with other agents. We operate under the assumption that certain agents may disrupt the system by disseminating inaccurate information, either due to flawed perceptions or conflicting interests within the community. Our model is segmented into three primary components (see Fig. 1):

Fig. 1. System model with three parts.

1. Collective information gathering system: This encompasses the collective and direct acquisition of information, considering the overall state of available information and the proximity to the ultimate goal. Coordination of collective activities is central to this system.
2. Communication system: This facilitates exchanges between agents based on the credibility of information and the trustworthiness of the involved partner.
3. Coordination of systems: Both information gathering and communication are intricately coordinated, wherein communication guides the gathering process and vice versa.

4.1 Direct Information Collecting System

The goal of any agent in the system is to collect information. Therefore, each agent stores the explored zone which contains all visited positions by itself and agents with which it has interacted. A position is considered as visited by agent i if it is or has been inside its perception range r_i. Once an agent has visited a position, it chooses the next position to aim by considering candidate positions which are on the border of the agent's explored zone according to well known algorithms. The choice of the next position is based on the following motion rules.

Rule of Random Motion. Utilizing a random strategy, the agent selects its next position randomly from the set of available positions. This rule comes into play when an agent either has no designated position to move to or has multiple positions with equal gains.

Rule of Motion Influenced by Distance. Agents are inclined to move towards the nearest border position. Each agent calculates the shortest travel distance *D(i, X)* from its current position to each border position *X*. The agent is more likely to choose a position to aim for if it has a smaller calculated distance value.

$$g_{dist}(i, X) = \frac{1}{D(i, X)} \tag{1}$$

Rule of Motion Influenced by Quantity of Information. The quantity of information *N(i, X)* of a specific border position is the number of data about the position *X* that agent *i* has collected. The smaller this value, the more agents tend to choose this position to visit. This is done in order to avoid the concentration of agents in the same places.

$$g_{info}(i, X) = \frac{1}{N(i, X) + 1} \tag{2}$$

Rule of Motion Influenced by Quality of Information. We assign an information reliability metric *R(i, X)* to each border position *X*, calculated based on the reliability of the information transmitters. Agents are more likely to visit positions with lower information reliability values, motivating them to verify areas with diminished reliability. This approach helps maintain coherence within the information system.

$$g_{reli}(i, X) = \frac{1}{R(i, X)} \tag{3}$$

Rule of Motion Influenced by Other Agents

The stronger the reliability of other agents, the more likely agents are to move in their direction. In this manner, agents tend to stay in proximity to trustworthy agents and move away from less reliable ones to access dependable information. The level of attraction or repulsion between agents i and j is determined by a vector:

$$\overrightarrow{F_{ij}} = \frac{T_{ij} - 0.5}{0.5} \times \frac{\overrightarrow{V_{ij}}}{D(ij)} \tag{4}$$

where T_{ij} where T_{ij} is the trust of i on j, $\overrightarrow{V_{ij}}$ is the vector from the position of i to the position of j, and $D(i, j)$ is the distance between i and j.

Let $A_{per}(i)$ be the set of agents in the perception zone of i which have an influence on the motion of agent i. The allocated gains for each border position X influenced by these agents is:

$$g_{agent}(i, X) = \cos(\overrightarrow{F}_i, \overrightarrow{V}_{iX}) \times \left|\overrightarrow{F}_i\right| \tag{5}$$

where $\overrightarrow{F}_i = \sum_{k \in A_{per}(i)} \overrightarrow{F}_{ik}$ is the final attractive/repulsive force of i on all considered agents, $\overrightarrow{V}_{iX}$ is the vector from the position of i to the border position X. The more the force $\overrightarrow{F}_i$ is strong, or the border position X is near the force's direction (the $\cos(\overrightarrow{F}_i, \overrightarrow{V}_{iX}) \times \left|\overrightarrow{F}_i\right|$ is bigger), the more strongly this gain reinforcements the agent to move to the border position.

The gain $g(i, X)$ for border position X for agent i is the weighted combination of these four measures (after normalizing) as shown in Eq. 6.

$$\begin{aligned} g(i, X) = {} & w_1 . \frac{g_{dist}(i,X)}{\max\limits_{Z \in P_{front}(i)} (g_{dist}(i,Z))} \\ & + w_2 . \frac{g_{info}(i,X)}{\max\limits_{Z \in P_{front}(i)} \left(g_{info}(i,Z)\right)} + w_3 . \frac{g_{reli}(i,X)}{\max\limits_{Z \in P_{front}(i)} (g_{reli}(i,Z))} + w_4 . \frac{g_{agent}(i,X)}{\max\limits_{Z \in P_{front}(i)} \left(g_{agent}(i,Z)\right)} \end{aligned} \tag{6}$$

where $P_{front}(i)$ is the set of considered border positions for agent i; $w_1 + w_2 + w_3 + w_4 = 1$ are the positive weights. By changing the weights, the importance of each rule can be changed: The higher w_1 is, the more agent i prefers to aim the border position which is the closest to it. The higher w_2 is, the more agent i prefers to aim the border position on which it has not enough information. The higher w_3 is, the more agent i prefers to aim the most unreliable border position. The higher w_4 is, the more agent i prefers to aim the border position which brings more chances to communicate with other reliable agents.

Finally, the set of the better candidate positions to aim X_{next} is constituted by the border positions presenting the maximum gain.

$$X_{next} = X_0 : g(i, X_0) = \max_{Z \in P_{front}(i)} g(i, Z) \tag{7}$$

In case of many X_0 satisfying the condition in Eq. 7, the next position to aim is randomly selected between these satisfactory positions.

4.2 Communication System

To gather information for mapping the region, agents have the capacity to directly assess the status of an area using their sensors. Moreover, they engage in communication with other agents to exchange knowledge, expediting the achievement of their objectives. Agents decide to communicate when at least one other agent is within their communication range.

The communication tendency can be considered on three levels:

- level 1: does the agent wish to communicate?
- level 2: if it wants, with which agent does it want to communicate?
- level 3: if there is a specific agent to communicate with, what information does the agent want to share with it?
- The following rules of communication answer to these questions.

Rule of General Tendency to Communication
The furthest the agent is from its aimed border position, the less the agent communicates. This rule forces the agent to reach its objective before considering communicating.

$$p(i) = \frac{D(X_{curr}, X_{next})}{D(X_{old}, X_{next})} \tag{8}$$

where $D(X_{curr}, X_{next})$ is the distance from current position X_{curr} of agent i to the selected border position X_{next}, $D(X_{old}, X_{next})$ is the distance from the old border position X_{old} of agent i (where i started to move) to the selected border position X_{next}. Intuitively, when agent i reaches its aimed border position X, this possibility is equal to 1. So the agent can communicate again. More precisely, nearer the agent comes to the aimed position, greater is the probability for it to collect reliable information on this position.

This rule answers to the question "Does the agent wish to communicate?". If the answer is yes, the next three following rules will determine with which partner the agent will communicate.

Rule of Communication Conditioned by the Reliability of the Communicating Partner. Agents communicate in correlation with the level of trust they have in their partners. The higher the trust among agents, the more inclined they are to engage in communication.

$$p_{reli}(i, i) = T_{ij} \tag{9}$$

where Tij is the trust that agent i has about agent j.

Rule of Communication Conditioned by the Duration of Disconnection. Agents tend to communicate in proportion to the duration between two consecutive communications, aiming to prevent redundant information exchange. The longer the disconnection duration between agents, the more likely they are to communicate.

$$p_{dur}(i,j) = \min\left(\frac{\Delta t_{ij}}{\underset{k \in A_{com}(i)}{\text{average}}\left(\Delta\prime t_{ij}\right)}, 1\right) \tag{10}$$

where Δt_{ij} is the amount of time spent since the last communication between i and j, $\Delta' t_{ik}$ is the amount of time spent between the last two communications between i and k. $A_{com}(i)$ is set of agents having communication with i.

Rule of Communication Conditioned by the Newness of Received Information
Agents tend to communicate to agents that send new information. The newer the received data is for an agent, the more this agent tends to communicate with the sender.

$$p_{new}(i,j) = \frac{1}{2}\left(\frac{n_j}{\max\limits_{k \in A^t_{com}(t)}(n_k)} + \frac{n_j}{n_j\prime}\right) \tag{11}$$

where n_k is the number of new data received from agent k (including j), n'_j is the total number of data received from j. $A^t_{com}(i)$ is set of agents having communication with i at the instant t.

The combination of Eqs. (9, 10, and 11) will determine the tendency of agent i to communicate with agent j:

$$p(i,j) = w_5.p_{reli}(i,j) + w_6.p_{dur}(i,j) + w_7.p_{new}(i,j) \tag{12}$$

where $w_5 + w_6 + w_7 = 1$ are positive weights. By changing the weights, the importance of each rule can be changed: The higher is w_5, the more agent i prefers to communicate with trustworthy partners. The higher is w_6, the more agent i prefers to communicate with long time disconnected partners. The higher is w_7, the more agent i prefers to communicate with partners that send more new data.

Once the tendency of agent i to communicate with agent j is determined, and if it wishes to, the following rules determine what information is communicated.

Rule of Communication of Direct Information. In a communication with partners, the more reliable are direct data, the more the agent tends to send them. In fact, the reliability of the direct data of an agent is computed from the trust of other agents on the agent itself. So, the more receivers trust this agent, the more the agent tends to send its direct data.

$$p(i, j, I_{dir}(i, X)) = T_{ii} \tag{13}$$

where $I_{dir}(i, X)$ is direct information of agent i about the position X, j is any receivers, T_{ii} is the trust of agent i has on himself.

Rule of Communication of Indirect Information. Similarly, the more reliable indirect data are, the more the agent tends to send them. Doing so, it contributes to the quality of the communicating system.

$$p(i, j, I_{ind}(i, X)) = reliability(I_{ind}(i, X)) \tag{14}$$

where $I_{ind}(i, X)$ is the indirect data that i has about position X, $reliability(I_{ind}(i, X))$ is the reliability of indirect data about position X that agent i received. The reliability reliability(*info*) of information *info* is calculated by the number of agents which provide the same value of *info* over the number of agents which provide information about *info*.

4.3 Self-organization in Control

As we formulate a self-organization approach encompassing two levels, we can outline a control system to interconnect these two organizational aspects and facilitate their co-evolution through self-organizing mechanisms. Consequently, the integration of the information collection system and the communication system unfolds as follows: behaviors related to collecting information are influenced by communication behaviors, and reciprocally.

Both systems are in fact very closely linked. For instance, behind rule 5 that seems only associated to the motion system, influences on the communication system can be detected. If an agent aims to go nearer to another agent, the probabiliity to communicate with it becomes greater.

Rule of Motion Reinforcement/Diversification Influenced by Accurate Information Reception. The more accurate data received from an agent are, greater is the tendency for the receiver to come closer to the transmitter. And the less accurate data received from an agent are, greater is the tendency for the receiver to go away from the transmitter

$$level_{reli}(i, j) = \frac{\sum_1^n C(I_{dir}(i, X), I_{dir}(j, X))}{n} \tag{15}$$

where n is the number of comparable data, i.e. data on the same position; $C(I_{dir}(i, X), I_{dir}(j, X))$ is the result of comparison between direct data of i about position X, and direct data of J from agent B on the same position X:

$$C(I_{dir}(i, X), I_{dir}(j, X)) = \begin{cases} 1 if I_{dir}(i, X) = I_{dir}(j, X) \\ -1 if I_{dir}(i, X) \neq I_{dir}(i, X) \end{cases} \tag{16}$$

Rule of Motion Reinforcement/Diversification Influenced by Newness of Information Exchanged

The more data received from an agent are renewed, greater is the tendency for the receiver to come closer to the transmitter. And the less data received from an agent are renewed, greater is the tendency for the receiver to go away from the transmitter

$$level_{new}(i,j) = \frac{1}{2}\left(\frac{n_j}{\max\limits_{k \in A^t_{com}(i)}(n_k)} + \frac{n_j}{n_{j'}}\right) - 0.5 \tag{17}$$

where n_k is the number of new data receipted from agent k (including j), n'_j is the total number of pieces of information receipted from j. $A^t_{com}(i)$ is set of agents having communication with agent i.

If we consider the previous rules indicating the impact of communication on motion, the attractive/repulsive force between agent i and agent j becomes:

$$\overrightarrow{F_{ij}} = \left(w_8.\frac{T_{ij} - 0.5}{0.5} + w_9.\frac{\sum_1^n C(I_{dir}(i,X), I_{dir}(j,X))}{n} + w_{10}.\left(\frac{1}{2}\left(\frac{n_j}{\max\limits_{k \in A^t_{com}(i)}(n_k)} + \frac{n_j}{n_{j'}}\right) - 0.5\right)\right).\frac{\overrightarrow{V_{ij}}}{D(i,j)} \tag{18}$$

where $w_8 + w_9 + w_{10} = 1$ are the positive weights. By changing the weights, the importance of each rule can be changed: The more w_8 is high, the more agent i prefers to approach to the partners who sent reliable data in the past. The more w_9 is high, the more agent i prefers to approach to the partners who sent reliable data just in the last transmission. The more w_{10} is high, the more agent i prefers to approach to the partners who send to it more new data.

Once the attractive/repulsive force between agent i and agents in its perception zone changes, the attractive/repulsive gain for each border position also changes by the Eq. 6. In other words, this represents the influence of communication on the movement of agents.

Algorithm 1 figures in a simplified way the main engine of an agent. The order according which agent's actions are executed is: collection of data (*lines 1–2*), communication (*lines 3–26*), motion (*lines 27–49*). In the communication part, the agent first of all determines whether it communicates (*lines 3–4*). If the answer is yes, it then finds partners to communicate with (*lines 5–11*). Once the agent has found partners to communicate, it determines which data are to be sent to its partners (*lines 12–14 and 18–20*) and then sends them (*line 15 and 21*). In the motion part, the agent checks whether it is at the chosen border position. If it is not yet, it moves on to the chosen border position. Otherwise, the agent must compute the next border position to aim. In this case, the agent calculates the gain for each considered border position (*lines 28–38*), including the gain associated to distance (*line 29*), to quantity of information (*line 30*), to position's reliability (*line 31*), and to other detected agents (*lines 32–48*). The position getting the biggest overall gain is then chosen as the next border position to aim (*lines 40–46*).

Algorithm 1. Algorithm for communication and movement of agent at each step

$X_{curr} \leftarrow$ the current position of agent i
collecting of data at X_{curr}
$p(i) \leftarrow \frac{D(X_{curr}, X_{next})}{D(X_{old}, X_{next})}$
if $flip(p(i)) = 1$ **then**
  avegare$(\Delta' t_i) \leftarrow$ *average of* $\Delta' t_{ik}$ for all agent k which is communicated with i at the instant t
  for all agent j in communication zone of i **do**
    $p_{reli}(i,j) \leftarrow T_{ij}$
    $p_{dur}(i,j) \leftarrow min\left(\frac{\Delta t_{ij}}{average(\Delta' t_{ik})}, 1\right)$
    $p_{new}(i,j) \leftarrow \frac{1}{2}\left(\frac{n_j}{max(n_k)} + \frac{n_j}{n'_j}\right)$
    $p(i,j) \leftarrow w_5.p_{reli}(i,j) + w_6.p_{dur}(i,j) + w_7.p_{new}(i,j)$
    if $flip(p(i,j)) = 1$ **then**
      for all direct data X of i **do**
        $p(i,j,I_{dir}(i,X)) \leftarrow T_{ij}$
        if $flip\left(p(i,j,I_{dir}(i,X))\right) = 1$ **then**
          send $I_{dir}(i,X)$ to agent j
        end if
      end for
      for all indirect data X of i **do**
        $p(i,j,I_{ind}(i,X)) \leftarrow reliability(I_{ind}(i,X))$
        if $flip\left(p(i,j,I_{ind}(i,X))\right) = 1$ **then**
          send $I_{ind}(i,X)$ to agent j
        end if
      end for
    end if
  end for
end if
if X_{curr} is the next border position X_{next} of i **then**
  for all considered border position X of i **do**
    $g_{dist}(i,X) \leftarrow \frac{1}{D(i,X)}$
    $g_{info}(i,X) \leftarrow \frac{1}{N(i,X)+1}$
    $g_{reli}(i,X) \leftarrow \frac{1}{R(i,X)}$
    for all agent j in the perception zone of i **do**
      $level_{trust}(i,j) \leftarrow \frac{T_{ij} - 0.5}{0.5}$
      $level_{reli}(i,j) \leftarrow \frac{\sum_1^n C(I_{dir}(i,X),\ I_{dir}(j,X))}{n}$

$$level_{new}(i,j) \leftarrow \frac{1}{2}\left(\frac{n_j}{max(n_k)} + \frac{n_j}{n'_j}\right) - 0.5$$

$$\vec{F}_{ij} = \left(w_8.\,level_{trust}(i,j) + w_9.\,level_{reli}(i,j) + w_{10}.\,level_{new}(i,j)\right) \times \frac{\vec{V}_{ij}}{D(i,j)}$$

end for

$g_{agent}(i,X) \leftarrow \cos(\vec{F}_i, \vec{V}_{iX}) \times |\vec{F}_i|$

end for

for all considered border position X of i **do**

$$g(i,X) = w_1.\frac{g_{dist}(i,X)}{max(g_{dist}(i,Z))} + w_2.\frac{g_{info}(i,X)}{max(g_{info}(i,Z))} + w_3.\frac{g_{reli}(i,X)}{max(g_{reli}(i,Z))} + w_4.\frac{g_{agent}(i,X)}{max(g_{agent}(i,Z))}$$

end for

$max(g(i,Z)) \leftarrow$ the biggest of $g(i,Z)$ for all considered border position Z of agent i

for all considered border position X of i **do**

if $g(i,X) = max(g(i,Z))$ **then**

$X_{next} \leftarrow X$

end if

end for

end if

5 A Case Study: Danger Mapping

5.1 Modeling and Simulation

We demonstrate our approach through a case study termed "Danger Mapping". In this scenario, we envision a swarm of localized mobile robots patrolling an uncharted territory. The goal for each robot is to construct the most comprehensive, accurate, and dependable map of the land while utilizing minimal resources. Robots possess the capability to directly ascertain the nature of nearby zones via their sensors. Additionally, they can communicate with other robots to exchange insights regarding the environment (the map) and fellow agents (trust).

The aim of this simulation is to showcase the emergence of organizations and roles within the system. Specifically, we focus on the emergence of roles at the exploration level, the communication level, and the retroaction between these two levels.

5.2 Results

Emergence in the Exploration System

In the 400 m × 400 m GIS (Geographic Information System) environment, we constructed 200 dangerous zones and positioned 50 agents with suitable ranges. This setup ensured that agents could encounter a diverse array of other agents during the experiment, facilitating the manifestation of system emergence and roles (see Fig. 2).

Among the predictable roles that emerge in the process of self-organization, we specifically focused on one of the fundamental roles: the explorer. Using the number of detected zones as a metric for each agent, we classified an agent as an explorer if the number of zones it detected exceeded the average number of detected zones for all agents in the system.

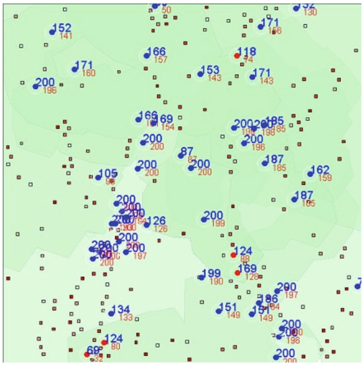


Fig. 2. Emergence in the system

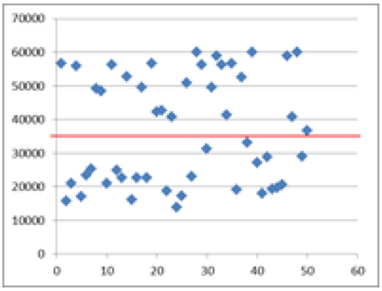


Fig. 3. Emergence of the explorer role

The results are shown in the Fig. 3 where the explorers are represented by points which are above the average line. The number of detected zones by explorers is significantly much higher than that of other ones ($M(explorer) = 52207$, $M(otherwise) = 22076$, $p < 0.001$, see Fig. 4).

Emergence in the Communication System

In order to observe emergence in the communication system, particularly the emergence of simple roles like transmitter or receiver, we introduced two indicators: the number of sent messages and the number of received messages for each agent. Therefore, an agent can be considered as a transmitter if it tends to send more messages than it receives. In the contrary, an agent can be considered as a receiver if it tends to receive more messages than it sends.

The results are shown in Fig. 5. The transmitters are represented by points which are above the middle line and the receivers are represented by points which are under the middle line. The emergence of these two roles are significant. In the role of transmitter,

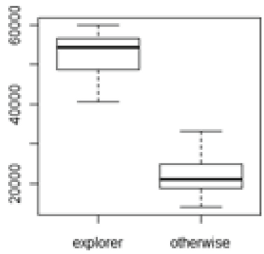


Fig. 4. Significant difference on the number of detected zones between explorer and others

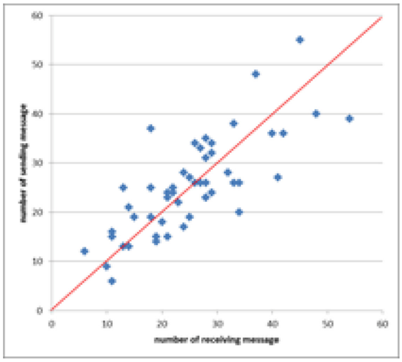
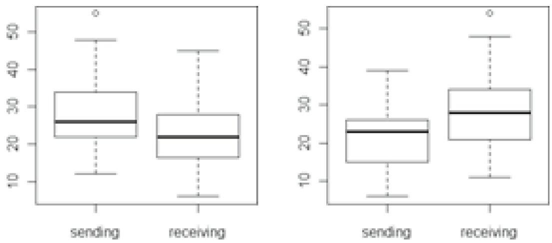


Fig. 5. Emergence of the transmitter and receiver roles

the number of sent messages is significantly higher than that of received ones ($M(sent) = 28.33$, $M(received) = 22.54$, $p < .04$, see Fig. 6.a). Inversely in the role of receiver, the number of received messages is significantly higher than that of sent ones ($M(sent) = 21.88$, $M(received) = 28.52$, $p < .02$, see Fig. 6.b).



a. transmitter role b. receiver role

Fig. 6. Significant difference on the number of sent and received messages: transmitter role 6.a, and receiver role 6.b.

Emergence in the Trust System

In order to show the emergence in the trust system, we consider two indicators: the trust of the agent on itself and the trust of the community on the agent (its reputation). The initial value of self-trust is 1.0, and that of reputation is 0.5. The more the agents trust an agent, the more the agent's reputation is increased, and vice versa. The more an agent recognizes that many agents trust it, the more its self-trust is increased, and vice versa.

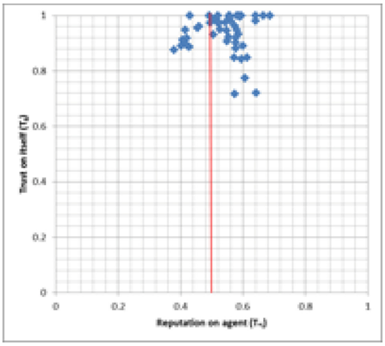


Fig. 7. Emergence of the reliable and unreliable agents

The results are shown in Fig. 7. On the reputation level, the reliable agents are represented by points on the right side of the middle vertical line, the unreliable agents are represented on the left side of the middle vertical line. The difference on the reputation between the two groups is significant ($M(reliable) = 0.576, M(unreliable) = 0.427, p < 0.001$, see Fig. 8). Unfortunately, there is no significant difference on the self-trust level between the two groups ($p > 0.7$): agents trust on themselves even if no other trusts on them. Actually, the simulation we implemented uses a number of interactions between agents that can be considered as few. Now an agent needs many negative advices to lower its self-trust and there were not enough of them. The same remark could be applied on the values of reputation that we got. They are not very far from the initial value 0.5. But they are enough for the demonstration so to distinguish between reliable and non reliable agents. The gap between the medium trust values could have been greater if the simulation could have lasted longer and offered many more transactions between agents.

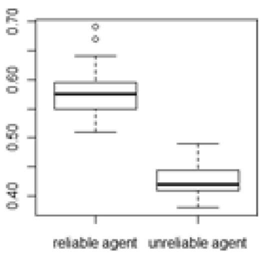


Fig. 8. Significant difference on the reputation between reliable and unreliable agents

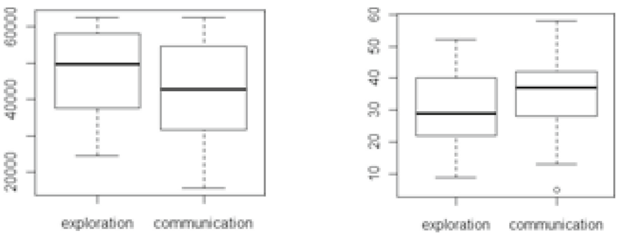
Emergence in the Exploration/Communication System

In order to observe emergence in the exploration/communication system, we launch two scenarios:

- The first scenario uses ($w_1 = w_2 = w_3 = 0.3$, and $w_4 = 0.1$). We expect that in this scenario, agents tend to explore their environment rather than communicate. We call this scenario as the exploration scenario.
- The second scenario uses ($w_1 = w_2 = w_3 = 0.1$, and $w_4 = 0.7$). We expect that in this scenario, agents tend to communicate rather than explore their environment. We call this scenario as the communication scenario.

In these scenarios, we use two indicators: the number of sent/received messages, and the number of detected zones for each agent.

Unsurprisingly, there are significant differences in both indicators which are measured in two scenarios. The number of detected zones in the first scenario is significantly higher than in the second one ($M(exploration) = 48102$, $M(comunication) = 42459$, $p < 0.04$, Fig. 9.a). Inversely, the number of sent/received messages in the first scenario is significantly lower than in the second one ($M(exploration) = 30.34$, $M(communication) = 35.78$, $p < .05$, Fig. 9.b). This results fulfill our expectations in the using of weights (w_1, w_2, w_3, w_4) in Eq. 6 to regulate the emergence.



a. The number of detected zones b. The number of exchanged messages

Fig. 9. Significant difference on the number of detected zones 9.a, and the number of sent/received messages 9.b between two scenarios

6 Conclusion

This paper introduces a self-organizational approach tailored for a multi-agent system, particularly one that operates in a disturbed state, utilized for distributed information collection. The approach adopts a systemic perspective, emphasizing a structural interconnection between two crucial levels: direct information gathering and communication. Specifically, a trust mechanism is integrated with localized behavior rules and environmental selective pressure, facilitating the emergence of two co-evolving organizations-social and spatial. The social organization mirrors the trust-based relationships developed among the diverse agents, while the spatial organization delineates the strategic deployment of agents in the environment to enhance inter-agent communication.

The local behavior rules encompass three primary categories: deployment rules, communication rules, and rules governing the interaction between communication and deployment. Our simulations experiment with a combination of these behavior rules to observe the emergence of organizations and distinct roles within the system. The outcomes demonstrate the emergence of a well-organized system and the delineation of roles across different levels: explorers in the direct data collection, transmitters and receivers at the communication level, and agents categorized as reliable or unreliable in the context of trust. Identifying the emergence of intricate roles that intersect the exploration and communication levels is an avenue for our future research endeavors.

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