

Does Communication Make a Difference?

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Abstract
This paper compares different animal groups from eusocial insect colonies to human society and discusses their mechanics and behaviour as agent systems. The main focus is on interaction between the agents and on how properties of a system like effectivity or predictability are affected by these interactions.

Keywords
Agent system, interaction, communication, emergence

1. Introduction

There are agent systems everywhere around us - from insect colonies through animals to human society and the economy. Being a part of an agent system means contributing to its behaviour and being affected by it in return. Although many natural systems share certain properties like information pooling (Couzin 2008) or collective decision-making (Conradt and Roper 2008), looking more closely unravels many questions about what different systems actually do and what influences behaviour of their members. Do termites build similarly shaped structures by purpose? Do all birds in a flock know what their direction is? Is a human crowd as naive in its movement as a herd of wild animals? How similar is behaviour of individuals in animal groups and more importantly, do forms of their communication make a difference to their system?

This paper will discuss different agent systems found in the nature and interactions that go on in these systems. The main aim is to define different systems through these interactions and compare their building blocks, effectiveness and dynamics.

2. Insects and Distributed Algorithms

We can understand social insect colonies as agent systems where (almost) identical units behave according to a set of simple rules. The colony exhibits behaviours not present in the individuals. Examples include ants that sort brood and dead bodies (Deneubourg et al. 1991) and are able to find the shortest path to a food source (Bonabeau E. at al. 2000), bee colonies able to choose the best from available food sources (Seeley et al. 1991), or termites that build structures up to 600 times larger than an individual (Theraulaz et al. 1998). It is remarkable that units are unaware of the overall result of their collective actions (Seeley et al. 1991, Theraulaz et al. 1998) but work together and affect each other’s behaviour through direct or indirect interactions.

In 1991 Deneubourg and his colleagues found two simple equations that could govern behaviour of sorting ants, more precisely the chance of picking up and dropping down an item during random movement based on perceived density of items around (Deneubourg et al. 1991). Their simulation work showed that the two rules were sufficient for artificial agents to behave like real ants when sorting. Beckers, Holland and Deneubourg (1994) even created robots that could sort pucks using similar rules.

Another ability of an ant colony apart from sorting is finding the shortest of available paths. Ants that are returning home leave pheromone trails on the ground. Because of the fact that pheromone evaporates, shorter paths are chosen by other ants that assess available routes based on the amount of pheromone. The ants drop pheromone again and the best choice wins progressively. (Bonabeau et al. 2000). Similar distributed algorithm can be used in computer science for the Travelling Salesman and other optimisation problems where a colony of agents is able to choose the best from available solutions (Bonabeau et al. 2000, Dorigo and Gambardella 1997).

Another example of optimisation by an agent system is a bee colony able to choose the best from a number of available food sources. Individual bees often visit one food source only and it is their genetically given ability to evaluate it sufficiently enough (Seeley 1991). Additional foragers are recruited in the nest based on strength of a bee's waggle dance. Positive reinforcement assures that eventually the best food source is chosen since more and more foragers dance for it. This technique is similar to the ants routing one, although there are some differences that will be discussed later. A similar principle plays role when bees are choosing a new nest place - positive feedback and distributed evaluation of possible sites lead to choosing the best one from a number of possibilities (Couzin 2008).

Furthermore, colonies of bees and termites exploit their strengths when building nests. Theraulaz et al. (1998) showed how different complex structures are progressively built based on simple rules genetically encoded in individuals. Similarly to sorting ants, building insects drop material with probability based on the state of their surroundings like existence of other walls in bees and terrain irregularities or queen's pheromone in termites.

Even though actions and movement of the insects is often random and based on limited local knowledge (Deneubourg et al. 1991), they were designed by evolution so that simple individuals benefit from being a part of a colony. Computer scientists can use the evolution's example to build agent-based systems that rely on reinforcement and feedback with simple behaviours at the individual level. Distributed algorithms are certainly attractive because of their effectivity, but are they the best and the only solution that the nature has? What are the details of interactions that go on inside and when do these systems fail? The rest of the paper will try to answer these and other questions.

3. Signalling vs. Stigmergy

When ants sort brood, they apparently do so on a very individual level. There is no explicit communication between them, although they still affect behaviour of others (probability of dropping or picking up an object) through changing of the environment. This type of interaction is called stigmergy (Grassé 1959 cited in Theraulaz et al. 1998) and could be regarded as indirect communication. Stigmergy is also utilised by termites and wasps when they build nests - again, there is a probability of dropping building material based on the surroundings constantly affected by other individuals.

Stigmergy can have some negative effects on the colony - sometimes ants sort against each other, especially if formed clusters are of similar sizes. Also, one can to some extent control the colony's behaviour by creating clusters or walls upfront, in which case ants will start forming their clusters around the pre-defined places (Bonabeau 1997). Similarly, termites start their nest building based on a 'template', i.e. an attribute of the environment like an uneven terrain or a (natural) wall (Theraulaz et al. 1998) that could be imposed by other species for their own advantage. Such systems are to a large extent 'under control' and there are no surprises than can happen when it comes to the result of their work - ants will always sort objects into similarly looking clusters and builder species will always build nests similar to others, both more or less on predictable locations.

There is another type of interaction that goes on for example in a beehive. For most of their tasks, bees recruit others through waggle dancing (Vries and Biesmeijer 2002, Seeley et al. 1991). It is questionable whether this is purely because they cannot leave pheromone trails for others in the air or whether there is another advantage to this approach. However, it is important to mention that there are differences between this interaction and stigmergy. Surely, there is still positive reinforcement (Sumpter 2006), but:

1. The waggle dance is based on a bee's individual perception of the quality of the source, i.e. two bees could signal in a slightly different way about the same fact. Signalling alters real data to a certain extent.
2. The signal is not 'always there' as with stigmergy - it arrives and leaves with its sender. Therefore, there need to be receivers present on a dance floor at the same time.
3. Foragers do not always signal, sometimes they go back to the food source (Seeley et al. 1991)

This means that action of an individual bee at a given time is less predictable than of an ant that simply assesses its environment where the information is always available and is unchanged by perception of others. Although a bee colony will find the best source *most of the times,* there are some less predictable behaviours that result from the facts above - namely cross inhibition and symmetry breaking, both investigated in simulation by Vries and Biesmeijer (2002).

Symmetry breaking refers to the fact that if bees are offered two food sources of the same quality and distance, they should exploit them symmetrically. However, when finding of receiver bees is introduced into the system, the symmetry breaks. Vries and Biesmeijer argue that this could lead to monopolisation of food sources if there were competing colonies, which could have a positive effect on both of them.
Cross inhibition occurs when sugar concentration in one of two equal sources suddenly increases. Again, due to the fact that waggle dance receivers need to be found, the colony as a whole sometimes concentrates on the less profitable food source.

Vries' and Biesmeijer's simulations demonstrate how adding a primitive form of signalling affects predictability of an agent system's behavioural outcomes. The result is more sensitive to chance (e.g. of a dancing bee finding a receiver bee or of a bee dancing at all and not going back to a food source), and cannot be easily predicted. Similarly to colonies that use stigmergy, the resultant behaviour is not just a sum of individual behaviours. However, in contrast with them, the landscape of possible results is more complex because of increased complexity of the behaviour and interactions between the individuals. We will examine properties and forms of emergence before looking at even more complex systems.

4. A Word About Emergence

Emergence is a phenomenon often discussed by scientists in relation to agent systems. In emergent systems there is always a set of agents with 'low-level' instructions and the whole that exhibits a 'higher-level output' (Forrest 1990) or less predictable behaviour (Cariani 1997) that cannot be observed by looking at one individual (Axtell 2006). Agents act using more or less simple sets of rules and the overall structure or goal are not addressed by the individual behaviours (Theraulaz et al. 1998). Holland (1998) refers to emergence as a phenomenon that occurs when individuals can learn or adapt and they affect each other, i.e. their behaviour is not affected by their immediate surroundings only.

(Cariani 1997) divides emergence into combinatory and creative. The first occurs in systems where a set of primitives combines and creates new structures out of existing ones. An example of such a system would be DNA where the same primitives (genes) can combine in a newly manner and create new characteristics of their bearers. On the other hand, 'creative' emergence involves creation of new primitives as a result of interactions of existing ones. Human mind would be an example of such a system - new thoughts and concepts emerge as a result of thinking, i.e. of manipulation of existing symbols. This type of emergence is more surprising and less limited as the new structures are not logical consequences of the previous ones. The amount of surprise seems to make the distinction between the two kinds.

There are two factors to consider when looking at an emergent system: complexity of its environment and complexity of interactions between its agents. Firstly, unpredictable external conditions can lead to surprising global behaviours. For example the fact that scouting bees or ants that represent only a small portion of the colony (Conradt and Roper 2008) could get killed on the way back to the nest adds to unpredictability of the colony's decision about a new nest site. Sometimes, probably most strongly in the economy, the system creates complex environment for the agents itself and complexity creates more and more complexity. In this case it is the interactivity of agents itself that leads to creation of structures. The structures are then propagated through the system and affect it, similarly to how its external environment does.

Interactions could be understood as 'motors' of agent systems that make them self-organise and create new structures within themselves. Moreover, this paper proposes that types of interactions determine to what extent a system is emergent and what structures (or type of emergence according to Cariani (1997)) can arise. This argument will receive more discussion in the following sections.
If we are to find emergent systems, we need to look at complexity of external environment of agents as well as of their interactions. If we are to model one, we need to give agents enough space to interact without specifying outcomes of these interactions. A system is truly emergent when we have to run it in order to say anything about its global level. Surely, some systems allow for extraction of 'rules of thumb' (economy (Axtell 2007) or a bee hive (Vries and Biesmeijer 2002)) or even mathematical rules like the central limit theorem (Sumpter 2006), but we need at least one working system to observe it for some time and understand its dynamics. In this respect, we could treat emergence as a quantitative rather than qualitative term. The more surprising outcomes a system can have, the more it is emergent.

5. Natural Agent Systems and Interaction

Before talking about interaction and communication, definitions need to be given. In the rest of the paper 'interaction' refers to any kind of exchanging information and/or influencing of behaviour between individuals. 'Communication' is understood as interaction that requires signalling, i.e. minimally a sender of a signal that is aware of sending some data to the outside world. This definition has been inspired by Philips and Austad (1996) and authors cited in their article. It imposes that communication is something intentional and involves individual's specific and distinguished actions such as waggle dance in honeybees or howling of a wolf.

Signalling in social insects

We could see from the example of honeybees how communication leads to more unpredictable systems than stigmergy because individuals' perception and situatedness are involved. Bees signal about a fact (for example quality of a food source), but the outcome is subject to unpredictable factors like a chance of finding receiver bees and competing with other recruiters that may or may not be there. On the other hand, stigmergy imposes information encoded in the environment that is more or less stable or at least available for sufficiently long time for any random trespassers (Deneubourg et al. 1991, Bonabeau E. at al. 2000). Also, 'senders' of information do not have the intention to communicate, interaction happens 'automatically'.

Flocks and herds

There is another type of interaction very similar to stigmergy, Follow the Neighbours rule. Many species use it to create flocks and to move in groups (Couzin et al. 2005, Couzin 2008) and even humans use it for example when a part of a crowd (Sumpter 2006, Couzin 2008). The common attribute with stigmergy is that there is no intention to communicate the movement direction, but individual agents form each other's 'environment' that is changed by their actions and affects other agents' behaviour. Therefore, the system's outcome is still more deterministic than emergent. Personal mood or preferences do not play much role in either of them since the behaviour is mostly encoded in genes (Couzin 2008). Couzin et al. (2005) researched the Follow the Neighbours rule in flocks and showed how the information is propagated through an agent system using bodies of individuals. For example in migrating fish, there are only a few informed individuals that set the direction and others follow, without explicitly knowing which of the individuals are informed. However, since the information about the way needs to be propagated through agents themselves not the environment, it can be more unpredictable as subject to propagation mistakes of individuals. For example, a bad direction taken by one agent can affect its neighbours and propagate through a portion of the group, even if the rest of the group follows the right direction. Especially birds sometimes break their flock and join again, forming dynamic and surprising shapes.

Signalling in vertebrates

Signalling about a fact evolved in many ways and in many species, from eusocial insects to vertebrates. In mammal societies it is usually a solution for cooperation in smaller animal groups where recognition of group members plays an important role and is maintained by grooming (Anderson and Franks 2001). Conradt and Roper (2008) suggest that direct communication between agents allows for complex group decision-making. This paper would like to add that signalling provides more emergent (unpredictable) systems than stigmergy. We already compared bees that signal and ants that use stigmergy. Let us now compare a colony of ants and a herd of wolves or lions that attack a prey. Ants all behave in the same way and any collective actions are encoded in their genes (Anderson and Franks 2001). On the other hand, mammals are taught by their parents and other group members how to behave and hunt. They use specific signalling to coordinate their activities (Conradt and Roper 2008). However, these signals could be disrupted by the environment or interpreted differently by different members. If an ant colony is stronger than its prey it is very likely to kill it. On the other hand, it is less likely and predictable whether a group of lions will catch an antelope - they must train together to achieve collective behaviour effective enough and to understand each other’s actions and signals. While signalling does provide an evolutionary advantage because of the speed of data propagation (Philips and Austad 1996), it involves individual learning. The systems are more unpredictable because their outcomes are subject to how well their members can learn, what stage their learning is at and to what extend they can coordinate their activities.

There is another important factor of signalling in vertebrates - metainformation usually transmitted as a part of a signal (Philips and Austad 1996). Metainformation contains message that is not subject to communication itself but provides additional facts about the sender, for example size of a toad based on its pitch of voice in a mating call or a location of an injured animal in an emergency call. Especially in humans, interpretation of the metainformation is subject to individual experience. Therefore, one’s reaction on such a signal can only be predicted statistically.

Human society

Human society is different from any other animal societies on the Earth. We are the only species that was able to achieve advanced tool making, international communication and create complex languages, culture, science and economy. If we evolved from apes, what factor provided such an evolutionary pressure to create something so emergent like the human society? Is there a difference in how early humans interacted?

(Chase 1999) argues that like other mammals, we live in relatively small groups but unlike in other species, the groups do not only consist of members of the same kin. Symbolic communication evolved because we needed to communicate with any member of our species, even ones that we did not meet before. We have culture and values like love or honour that enforce our cooperation because of our evolutionary need to cooperate (Chase 1999, Chase 2006). Also, even though exceptions exist, we can resolve our conflicts easier by reasoning, negotiation and established rules. This can have a significant positive impact on any agent system (Clutton-Brock and Parker 1995)

Symbols do not only help us to communicate complex plans and facts but also to learn more quickly. We do not simply learn every possible situation like most of the apes (Chase 2006). Instead, we learn ‘principles’ that can be applied to many situations and more importantly combined to produce new solutions. In this respect we are less limited in what we can make and learn and the emergence in our society is creative according to Cariani’s classification (Cariani 1997).

Many authors agree that language may have evolved to maintain large number of relationships we have (Dunbar 1993 cited in Key and Aiello 1999). Also, it was shown that humans and chimpanzees try to manipulate thoughts and actions of others through communication and relationships in order to minimize the chance of being deceived. This is a very important factor for example in economy where we are constantly trying to maximize our profit by interaction with others (Axtell 2006). It is the negotiation rather than immediate execution upon a signal and individual interpretation of sometimes highly abstract symbols as means of communication that provide high unpredictability to our groups and make the human society so emergent.

Economy is indeed a very interesting agent system in its own respect. Classical neoeconomy tries to model the market via isolated agents that communicate through abstract economic variables like price

(Axtell 2007) and therefore in many respects provides stigmergic explanation of the economy's dynamics. Surely decision making of agents in such a model is more complex than in insect colonies, but as Axtell (2007) argues this approach is not sufficient enough. His network approach suggests that there are social interactions between individuals and their groups (for example firms) and that through these interactions agents try to manipulate others and find out as much information as possible to maximize their own profit (or profit of their group). Moreover, he suggests that people do not have perfect information about the global market, hence actions of the economic agents are mostly based on beliefs. Such a model is highly emergent since beliefs are very individual and depend on one's history, values and especially dynamics of an environment one was exposed to.

It is probable that similar factors (beliefs, values and individual preferences) play role in all human-human and human-animal interaction. Therefore, interaction with a human is highly unpredictable and cannot be modelled easily (let us again contrast with a bee hive that has already been modelled and behaved similarly to a real one). Indeed, there are only very few good models of the economy (Axtell 2006) and no models of a human society as a whole known to the author of this paper so far. Ironically, even if we had a perfect economical model where we could input parameters and predict how the stock market would look like in a few years, the model would loose its purpose if everybody possessed it. All agents would behave based on perfect predictions and the real system would evolve in a completely different direction than its model would have predicted.

6. Levels of Interaction

To sum up the discussed differences between the agent systems, three main levels of interactions are proposed. The ants sorting behaviour is translated into the different levels for better understanding and comparison of a system's outcomes.

Level 1: a) Stigmergy

Example: brood sorting based on random movement and brood density. Outcome is rather deterministic; agents follow simple and predictable rules.

b) Follow the Neighbours

Level 2: a) Signalling about a fact

Example: an ant creates a signal about a density that needs attention. Sorting is likely to be more effective, but this would depend on how many ants would follow the signal and how many ants would be signalling at the same time.

b) Signalling about an Intention

Example: ants also signal about where they will be dropping brood.
Sorting is likely to be even more effective, although unpredictability would probably stay the same because of the factors mentioned in 2a.

Level 3: a) Collective planning

Example: When multiple ants detect a signal about brood density, the colony negotiates which individuals will head to the location. Effectivity is increased by more even distribution of the work force.

b) Symbolic communication (defined through a) awareness of mental state of others in interaction or b) understanding of 'principles' rather than one-to-one relationships between action and cause in learning (Chase 2006))

Example: ants can effectively coordinate their intentions and actions through manipulation of symbols like direction or brood density estimates during communication. They can learn principles of sorting and are likely to find new strategies for increased effectivity.

Figure 1 compares emergence and effectivity of agent systems that use the different levels of interaction and the table below lists their properties.

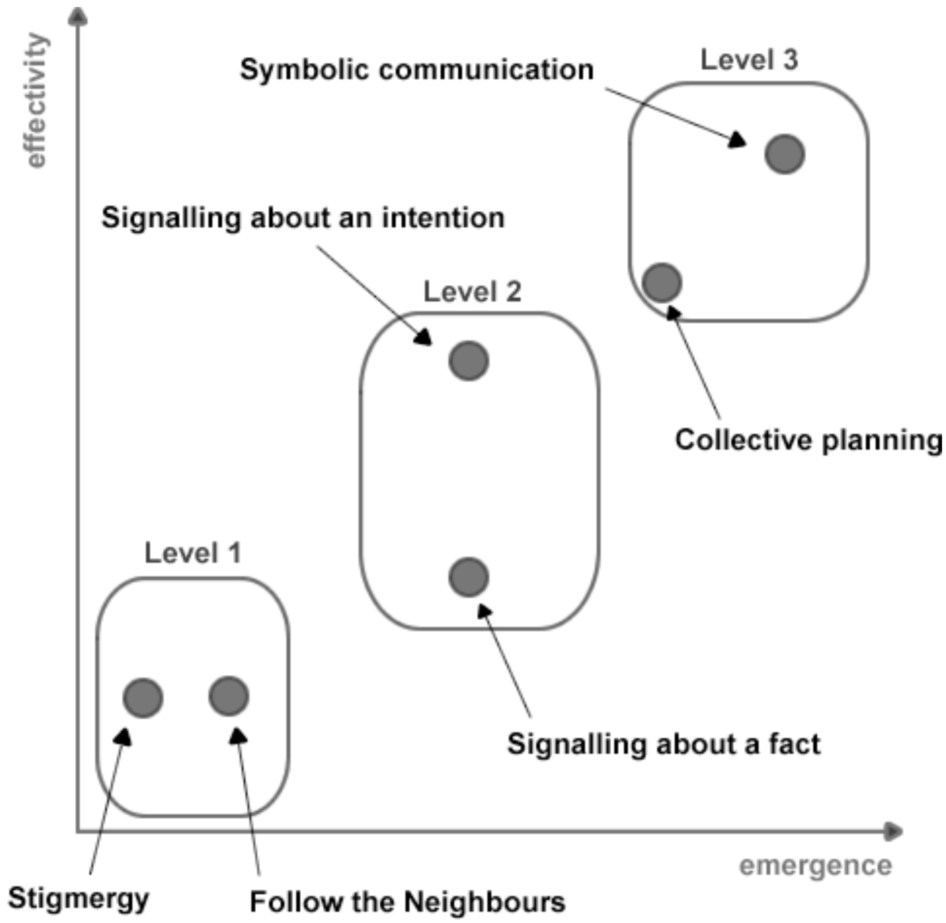

Figure 1

Property	**Level 1**	**Level 2**	**Level 3**
Behavioural rules	Encoded in genes	Encoded / learned	Learned
Teams	Recognised individuals usually of the same kin	Recognised individuals usually of the same kin	Any individuals, not even necessarily of the same species
Team decisions	Combined	Non-forced consensus	Consensus, forced if necessary
Information flow	Propagation	Interpretation	Interpretation

The **behavioural rules** and how symbolic communication allows for **teams** of non-related individuals were already discussed above.

In terms of **team decisions**, the division into combined and consensus decision-making was suggested by Conradt and Roper (2008) In combined decision-making all individuals contribute to the decision and self-organisation occurs. For a group to reach a consensus, only a few informed individuals that affect decisions of other team members are needed. In mammal societies strong individuals (usually decision makers) are not able to enforce their decisions if there are large and permanent conflicts between group members and such teams loose effectiveness (Conradt and Roper 2008). On the other hand, human society provides means of enforcing decisions of leaders through laws and symbolic statuses of people like policemen.

Information flow refers to how data is distributed through the system. Propagation means that the information is simply copied and there is a small chance it will be altered (this applies to e.g. Follow the Neighbours rule) (Couzin et al. 2005). Interpretation involves individualism and occurs when there is a signal to share in a group - each member can alter the signal slightly and depending on the number of agents that the signal goes through, original information has a certain level of noise that can be interpreted differently by different individuals.

It is important to note that animal species are not strictly divided into the three categories. Although social insects can exhibit maximally 2nd level and some of them only the 1st, species that evolved interactions on 2nd or 3rd level also use interactions from lower levels in certain cases (for example behaviour of a human crowd or of building bees, both discussed above). Also, it is possible that if we would understand agent systems as organisms themselves, they could exhibit higher-level interactions with other super organisms of the same kind. For example, (Anderson and Franks 2001) mention how an ant colony signals its strength to another colony through forming a line of workers in front of it. Similarly, there are signals travelling between cells of human brain, but the brain as a whole is able to understand and manipulate symbols, even though we cannot say that neurons ‘understand’ the meaning of a symbol.

Finally, the higher the level of interaction the more emergent the system is. This relates not only to predictability of the outcome but also to volume of possible outcomes. While ant colonies are quite limited in what they can do, human society seems to have unlimited options as a result of people’s creativity and more importantly interactions between creative people. Structures that are formed in our society vary throughout the centuries and the more complicated our society is the faster its progress seems to be.

7. Does Higher-Level Communication Help?

If we were building social robots, would we use stigmergy or signalling as the main means of their communication? Surely it would be less expensive to build ant-like robots, but as with ants their collective actions would be limited to what they were pre-programmed to do. Even if they could adapt to a dynamic environment, the change would be slow and difficult to communicate throughout the colony. Secondly, stigmergy relies on random movement that the author sees as the main problem of the approach. Even though distributed systems that rely on ant-like agents compete well with other algorithms used in computer science (Bonabeau et al. 2000), their effectivity could certainly be improved by signalling about found facts or even more by negotiation of future actions. This would however come with higher programming, engineering and computational costs.

If we managed to implement a form of symbolic communication, we could potentially open a door to creation of a robot society. Their learning would be improved and their communication could reach level of humans or even beyond. However, how much under control would such a system be? Could we still give it a task that would always be fulfilled? Like humans, collective robots could definitely do more tasks faster because of effective division of labour, but would they still want to do them if it was not for their own benefit? Chase (2006) argues that symbolic communication needs the participants to be aware of mental state of each other. Surely for that to happen one must first be aware of himself as a thinking and ‘living’ entity. Does this mean our robots would have their own personal goals, preferences or even 'souls'?

It is questionable why social insects and in fact all species did not develop symbolic communication or at least forms of signalling that would speed up their actions as a colony. Signalling allows for teams of specialists and complex societies, which is a factor important in vertebrates because of usual small size of their groups (Anderson and Franks 2001). Size of groups seems to be one of the factors when it comes to evolution of interactions. There was probably no pressure for social insects to evolve complex communication. However, signalling evolved where there was no way for stigmergy to work, like in bees. Finally, symbolic communication seems to have taken place when there was a capacity in the bran for it and a strong pressure on cooperation, like in early human hunters in the environment with little food.

8. Conclusion

Starting with eusocial insect colonies, this paper compared different levels of interactions in natural agent systems, from stigmergy and primitive signalling to symbolic communication. Different forms of interactions evolved in different species because of evolutionary pressures or constraints of their natural environments. It was shown how more complex interactions affect agent systems in terms of their unpredictability and volume of possible outcomes and how systems with high-level communication are more emergent. Finally, there was a discussion about what impact symbolic communication could have on distributed robot systems and whether it would be effective to implement it.
The assumptions of this paper are purely theoretical and simulation work would need to confirm whether communication does indeed make a difference, although contemplations about this question seem to impose it. Systems of agents with the same topology and tasks but different means of interactions need to be examined and their outcomes and effectivity compared. Also, apart from find out whether the systems would be much different or not, explanation of why species on the Earth evolved so many different means of interaction needs to be found. It is questionable whether simulations would help in this endeavour - they would have to be based on extensive historical data and their complexity would have to be managed to filter out unimportant factors.

Nevertheless, a fact remains that structures and capabilities of different natural agent systems vary and interactions that go on inside of these systems seem to be a factor in deciding their behaviour, dynamics and outcomes.

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