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## On the Role of Stigmergy in Cognition

Luís Correia · Ana M. Sebastião · Pedro Santana

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Abstract Cognition in animals is produced by the selforganized activity of mutually entrained body and brain. Given that stigmergy plays a major role in self-organization of societies, we identify stigmergic behavior in cognitive systems, as a common mechanism ranging from brain activity to social systems. We analyse natural societies and artificial systems exploiting stigmergy to produce cognition. Several authors have identified the importance of stigmergy in the behavior and cognition of social systems. However, the perspective of stigmergy playing a central role in brain activity is novel, to the best of our knowledge. We present several evidences of such processes in the brain and discuss their importance in the formation of cognition. With this we try to motivate further research on stigmergy as a relevant component for intelligent systems.

**Keywords** Stigmergy · Self-organization · Swarm · Cognition · Neurons · Artificial Intelligence

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L. Correia

E-mail: Luis.Correia@ciencias.ulisboa.pt

A. Sebastião

Instituto de Farmacologia e Neurociências, Faculdade de Medicina, Universidade de Lisboa, Portugal Instituto de Medicina Molecular, Universidade de Lisboa,

Portugal

#### P. Santana

Instituto de Telecomunicações, Lisboa, Portugal

ISCTE - Instituto Universitário de Lisboa, Portugal

#### **1** Introduction

Swarm models are one of the most recent approaches to cognition. They naturally map the cognitive capabilities of animal collectives such as termites as studied by Turner (2011b), and they can also support individual cognition, as shown in a realisation on mobile robots by Santana and Correia (2010). In the former case we are in presence of cognition of the colony, which is situated at a larger scale, when compared to that of each individual. In the latter case the swarm model forms the perception of cognitive concepts by a single agent, the robot controller, which is external to the swarm.

Common to both cases above is the collective impinging on the individuals' behavior and a strong embodiment in the sense of the interaction of the individuals with their environment. In fact, this bidirectional influence is such an important feature that it is associated to the definition of cognition in general by Bitbol and Luisi (2004).

Swarm models of cognition based on a particular form of interaction with the environment that allows indirect communication between individuals is also common. It is denominated *stigmergy* (Theraulaz and Bonabeau, 1999). In short, each action of an individual, as a result of his perception of the environment, will change that environment, which will result in a different subsequent perception, in a process that repeats for each and every individual.

The work of Trianni et al (2011) presents a clear case for swarm cognition as a unifying model ranging from the formation of individual cognition to the cognitive capabilities of human and other animal societies. However the concept of stigmergy is not even mentioned in such article. In this paper we focus on the generality of stigmergy for cognition, ranging from social systems

BioISI, Faculdade de Ciências, Universidade de Lisboa, Portugal

to the brain activity. While the former are usually associated to and given as examples of stigmergy, brain activity has not been analysed in such a perspective. Doing so we believe it may provide new insights to the cognitive processes and we motivate further research on this subject.

The next section presents a working definition of stigmergy and a brief analysis of its properties. In section 3 we review a variety of natural collective systems and the way they use stigmergy to support their social cognitive capabilities. Section 4 presents significant work using this concept to produce cognitive knowledge in artificial devices, namely robots. In section 5 we analyse expressions of stigmergy within an individual, with special concern to the neuronal system. A concluding section follows stressing the key points of this work.

#### 2 The ubiquitousness of stigmergy

The term *stigmergy* was coined by Grassé (1959) while studying the nest building behavior of termites. Currently, the concept extends to a variety of human society activities, from those as involuntary as trail formation to the ones as goal directed as scientific research (Parunak, 2005). According to Heylighen (2016a), its definition can be expressed as follows:

stigmergy is an indirect, mediated mechanism of coordination between actions, in which the trace of an action left on a medium stimulates the performance of a subsequent action.

The understanding is that any action is not a functional entity but rather something produced by an agent. In this case, agent is a term we use as a generic designation for the different types of active individuals that form some collective (cells, ants, humans, ...).

A couple of notes are relevant at this point. To avoid blurring definitions we may not consider direct interactions to contribute to the stigmergic quality of a system. The second aspect is related to the type of medium. The usual assumption is that the medium is passive, meaning that it does not modify the traces. However this has to be taken in a loose way, meaning that the changes in the traces when left to themselves are at a slower scale than that of the changes made by the individuals leaving the traces. But once we consider that the medium has some effect over the traces the door is open for dynamic media, which in the extreme may be constituted by a population of other type of agents<sup>1</sup>. Without going to extremes we consider the medium and the traces to be minimally active in the sense that the traces dissipate with time if not renewed. Actually this is enough to produce the dynamics that stigmergy necessarily carries.

In a series of two articles Heylighen (2016a) and (Heylighen, 2016b) reviews a variety of cases and analyses this mechanism in detail. It is ubiquitous with materializations ranging from physics and chemical reactions to human organizations. A relevant aspect is the self-organized quality of the systems where stigmergy exists. Not all self-organized systems need stigmergy. However, all stigmergic systems are self-organized.

Although stigmergy may be exploited by single individuals, it is mostly considered in collective systems, with many individuals. The traces left in the medium may be interpreted as a form of collective memory, with varying persistence. In computer science terms, traces can be considered as global variables, that can be read and updated (in small changes) by each individual<sup>2</sup>. Such memory, external to the individuals, can support from simple decisions as in slime mould navigation (Reid et al, 2012), to more complex forms of human organizations (Marsden, 2013).

Surprisingly we do not find any reference to the diverse stigmergic processes in the brain that ultimately support cognitive capabilities. Heylighen (2007) associates quantitative stigmergy to the Hebbian type of learning (Haykin, 2007) that models synaptic connections strength in the brain, and qualitative stigmergy<sup>3</sup> to working memory and external traces. However, these are not the only stigmergic processes in the brain, and are possibly not the most representative ones. In our opinion these are not typical stigmergic processes since the communication involved in the learning process is direct among the cells and not through a medium. As we have previously noted, direct communication may not qualify a system as stigmergic.

In all the reviewed literature about stigmergy the focus is on the social interaction of autonomous individuals, be them unicellular organisms or humans. The way individuals communicate, self-regulate, and produce new knowledge by means of an external medium is the common object of study. However, stigmergic processes exist also internally among the cells of any single individual. According to Theraulaz and Bonabeau (1999), Herbert Spencer in the 19th century considered that any society is an organism. Here we are defend-

 $<sup>^1</sup>$  Werfel (2006) uses the term  $extended\ stigmergy$  to designate such cases.

 $<sup>^2\,</sup>$  Traces left on their own are subject to environmental degradation and will eventually fade out.

 $<sup>^3\,</sup>$  "Quantitative" describes changes in existing representations and "qualitative" describes creation of new representations.

ing its converse: any organism is a society<sup>4</sup>. In doing so we look at some of the stigmergic processes going on within an individual contributing to the homeostasis of the subject. We are particularly interested in this type of interaction within the brain, namely in the contribution for the cognitive capabilities of the individual. In fact, we argue that stigmergic processes are fundamental to form the cognitive capabilities of an intelligent individual.

#### 3 Swarm Cognition in Nature

Stigmergy is ubiquitous in insect societies, often realised via pheromone-based interactions. For instance, by exploiting pheromone-based local interactions, army ants are able to forage large areas around their nest in a parallel and robust way (Deneubourg et al, 1989). The coordinated operation of the ant colony as a whole and its ability to robustly cope with the environmental context have lead researchers to consider the colony as exhibiting a sort of collective intelligence (Franks, 1989), as if the whole colony was a *superorganism*. Recently, this connection between swarm behaviour and cognition has been studied more deeply under the token of *swarm cognition* (please refer to Trianni et al (2011) for a survey).

When foraging, ants deposit pheromones along several concurrent trails with the purpose of recruiting more ants towards the most promising foraging sites. The competition that emerges between pheromone trails resembles the lateral inhibition that one can easily find between neural circuits, key for spatially selective visual attention tasks (Couzin, 2009). Ants maintain several trails as a way of concurrently explore/exploit different regions of their environment, which mapped to human cognition should suggest that humans could maintain concurrent attention between competing stimuli. As pointed out by Santana and Correia (2010), this is in accordance to the multiple covert attention hypothesis in humans (Pylyshyn and Storm, 1988) and (Doran et al, 2009), which states that we are able to perform concurrent search for multiple objects in our visual field.

The decision between which trail to follow requires ant-level decision-making. Colony-level decision-making emerges as a result of these local decisions (positive feedback) and pheromone evaporation (negative feedback). The interplay between these two major factors imposes a speed-accuracy trade-off (Couzin, 2009), whose

neural basis in humans have been already studied by van Veen et al (2008). Selecting among several options under noisy observations and considerable time pressure is what ants and honeybees often face when picking a new location for their nests, amongst several candidate locations. In short, scouts search the environment for putative new locations for their nests, whose locally assessed quality is used to recruit more or less scouts to each location. As a result, more promising locations are visited more often by more individuals than less promising locations. In a way, the swarm is deploying its "attention" selectively across the swarm's "field of view" while maintaining a short-term group memory (Passino et al, 2008). Eventually a threshold is reached and the colony migrates to the selected location, implementing a winner-take-all process resembling the ones found in neural systems (Passino et al, 2008). Interestingly, there is evidence that this is a statistically optimal collective decision-making process, very similar to what happens in primate brains, via direct competition between evidence-accumulating populations (Marshall et al, 2009).

Although not always obvious, but there is a continuous effort for mapping the physical elements of swarms and neural structures found in human brain. The pheromone deployed by ants during their foraging activities can be though as a distributed memory. As pointed out by Couzin (2009), short-term and long-term memories are implemented by ant colonies via the use of multiple pheromones with different evaporation rates. Couzin (2009) also maps the strengthening of frequently used trails to Hebbian reinforcement of active neuronal pathways through long-term potentiation and highlights several striking similarities between ant colonies and neural networks as parallel information-processing systems. In a similar context, although not involving stigmergic behaviour, Passino et al (2008) go a step further and refer to neurons as the analogous of bees in swarm cognition and to action potential as the analogous of the bee's dancing strength when recruiting other bees in the nest.

Until now we have discussed stigmergy as the means for self-organised *information processing* in a cognitive system. Stigmery allows swarm individuals to coordinate their activity to create a sort of collective mental representations of the environment. The pattern of foraging pheromone trails deposited by an colony can be thought as representing the distribution of food sources and their relative quality. This distributed representation is then used by the colony individuals to determine their actions, the same way humans reason on top of world representations built from sensory feedback. However, a truly cognitive system is not only

<sup>&</sup>lt;sup>4</sup> Minsky (1988) proposed the idea of the mind as resulting from a set of agents working together in a kind of society, although without taking into account self-organization or stigmergy.

able to produce environment representations through self-organised *information processing* of sensory input, it must also be able to develop these information pro*cessing structures* from the bottom-up. Interestingly, as we will see, there is evidence that social insects are able to produce such structures, meaning that they can also help us understanding how developmental processes can be self-organised in a cognitive system. In particular, Turner (2011a) describes the mounds built and maintained by termites through stigmergic processes as sophisticated filtering devices, whose function is similar to the one of the optical structures of the eye. However, rather than producing two-dimensional images as an eye would, a kind of three-dimensional map of turbulent air perturbations is produced by these mounds. This filtering process enables respiratory gas exchange in the termite colony and drives the mound construction and repair processes. In this case, stigmergy works as the engine for self-organised development of perceptual structures key for the cognitive system to be able to interact with the environment.

As we have seen, social insects, greatly thanks to stigmergy, are able to robustly entrain their activity with the one of the environment, thus behaving adaptively. However, despite the sheer complexity exhibited by these social insects, we can hardly state that their collective cognitive capabilities match the ones of higher order animals. This is particularly true if the comparison is done against humans, whose presumably openended learning capabilities still far surpass our comprehension. Therefore, we must find traces of learning capabilities in social insects if the analogy between swarm cognition and human cognition is to endure. Leadbeater and Chittka (2007) survey several studies indicating cases of insects, including ants, provided with a remarkable repertoire of social learning capabilities. Some of these studies also suggest the presence of minimal culture among some social insects, in the sense that learned knowledge is transferred across generations. The insights obtained from observing the plasticity present in social insects and how it affects the global behaviour exhibited at the colony level can help us understand how we are able to self-organise highlevel concepts from low-level associatively learnt fragments.

#### 4 Artificial Swarm Cognition

Swarm cognition exhibited by social insects has inspired the development of artificial life systems exploiting such property (please refer to Trianni et al (2011) for a survey). Despite their value for practical robotic applications (e.g., (Santana and Correia, 2010) and (Santana and Correia, 2011)), these systems allow the study of cognition by building it, in line with the synthetic approach to embodied cognition (Pfeifer and Scheier, 2001) and (Pfeifer and Bongard, 2006) and artificial life (Bedau, 2003).

Swarm intelligence (Bonabeau et al, 1999) is a field of artificial intelligence that exploits the remarkable heuristics exploited by social insects to develop powerful general-purpose optimisation and search meta-heuristics. Swarm robotics (Brambilla et al, 2013) is a related field that borrows the self-organising properties exhibited by the social insects to build robust multirobot coordination strategies. Swarm intelligence metaheuristics, most often related to the stigmeric behaviour exhibited by army ants, have been employed for the development of computer vision systems (Poli and Valli, 1993; Owechko and Medasani, 2005; Mobahi et al, 2006; Broggi and Cattani, 2006; Zhang et al, 2008; Santana et al, 2013). These systems are, to a large extent, standalone engineered parallel perceptual solutions, lacking an interaction with action selection and mapping processes. This deficit undermines the system's explanation power regarding the mechanisms actually building up cognitive behavior.

To close the gap between swarm cognition and individual cognitive behaviour, Santana and Correia Santana and Correia (2010) and (Santana and Correia, 2011) studied how the stigmergic behaviour displayed by foraging army ants could be employed to implement robot behaviour in natural environments. The study encompassed the development of a control system composed of a set of simple virtual agents inhabiting the robot's visual input, called p-ants. Similarly to real ants, which need to collectively forage their environment for food (Deneubourg et al, 1989), p-ants implement multiple local covert visual attention (Pylyshyn and Storm, 1988) and (Doran et al, 2009) loops deployed to search the robot's visual field for obstacles. Global spatio-temporal coherence of the visual search task is ensured by the swarm's self-organized collective behaviour emerging from stigmergic interactions mediated by virtual pheromones. Experiments showed the ability of the system to robustly control an off-road robot equipped with a stereoscopic vision sensor in a local navigation task with less than 1% of the robot's visual input being analysed.

In line with the active vision approach (Bajcsy, 1988), (Ballard, 1991) and (Sporns and Lungarella, 2006), pants are modulated by the robot's action selection process in order to deploy visual attention in a by-need basis. Modulation is done by recruiting more p-ants to the regions of the robot's visual field where the presence of obstacles is expected to produce the most impact on the action selection process. For instance, if, due to task constraints or current knowledge about the world state, the action selection process outputs a right turn, visual attention increases preference for the right-hand side of the robot's visual field. This preference is set under the rational that an obstacle detected on the left-hand side would have lesser impact on the unfolding of both action selection process and actual robot motion. With the goal of better covering and tracking obstacles, pants are also recruited when new obstacles are found. Hence, the number of recruited of recruited p-ants is a function of the action selection (task) needs and complexity of the environment (obstacles distribution).

The swarm-based visual attention system is in fact performing a biased parallel stochastic sampling of the environment. The biases come in the form of a modulatory signal provided by the action selection process and of virtual pheromone laid down by p-ants for their coordination. This parallel stochastic sampling procedure enables a progressive parallel allocation of computational resources whose distribution density approximates the obstacles distribution in the visual field and action selection demands. The speed-accuracy trade-off is naturally handled by controlling the rate of p-ants being recruited into the robot's visual field and virtual pheromone properties (e.g., evaporation rate). As the analysis is progressively improved in parallel, the system is able to deliver good-enough results upon request, which is key to handle dynamic environments and tasks.

The system maintains spatial memories that can be said to be simultaneously implicit, active, parallel, and sparse. Short-term memory is implicitly represented by the virtual pheromone deployed by p-ants when searching for obstacles in a coordinated way. As the robot moves, p-ants actively track obstacles to reduce re-detection time. Eventually, p-ants move outside the robot's field of view, being their position updated according to robot's ego-motion estimates. In the latter case, p-ants become long-term sparse active spatial memories of the local environment. When the same environment is revisited, these p-ants (memory elements) become active in the robot's visual field of view, resuming their usual operation.

Control systems inspired by the swarm cognition exhibited by social insects imply the use of agent-based design. Each agent is modelled according to the known rules of their natural counterparts and adapted to meet a set of engineering requirements. Neuro-evolution (Floreano et al, 2008) can be employed to aid the system designer in this process, in particular when it is not obvious how to implement agents that, when put together, should produce the desired global behaviour. In this case, neuro-evolution operates on a small pa-

rameter space, the one of the agent. The small size of the parameter space owes to the fact that the system's global behaviour is an emergent property, requiring no explicit coding. Conversely, if neuro-evolution would to operate on a monolithic system, then both local and global behavior would have to be taken care simultaneously and explicitly, resulting on a much larger parameter space. Hence, we argue that an agent-based design, promoted by the swarm cognition framework, tends to foster tractability and scalability of the control system. Moreover, the computational models being already parallel by design, match directly with computational parallel architectures (e.g., GPU). Remarkable results along this line of work have been recently obtained in the application of Particle Swarm Optimisation (PSO) (Kennedy, 2011), a well known meta-heuristic inspired by animal collective behaviour, with GPU-based pose estimation and tracking of human hands using the Kinect sensor (Oikonomidis et al, 2011).

Santana and Correia (2010) proposed that, rather than static structures, as neurons are, these swarm individuals (agents) are better viewed as active information particles that flow through the cognitive system. This agent-based abstraction allows us to map swarm cognition concepts to human cognition by focusing more on the cognitive processes than on their supporting substrate. In line with research in active perception (Bajcsy, 1988), (Ballard, 1991) and (Sporns and Lungarella, 2006), being sensorimotor coordinated units, these information particles can use their sensorimotor history to induce long-range influences on other information particles, actively select and shape their sensory input to increase pose invariance, signal-to-noise ratio, and discriminative power. When together, these modular units can exploit the synergy of self-organisation and emergent properties, in line with the dynamical systems approach to human cognition (Beer, 1995) and (Thelen and Smith, 1996). Bearing these properties in mind, Santana et al (2013) proposed an hybrid neural-swarm perceptual cognitive model, in which neural-based layers are exploited to realise low-level processing of the agent's sensory input, as it demands mostly for massively parallel, dense, local, and isotropic spatio-temporal processing, whereas a stigmergic swarm-based layer is exploited for higher-level perceptual reasoning, as it demands for sparse, global, and anisotropic spatio-temporal processing. We think that an agent-based modelling of human cognition (Minsky, 1988), (Chialvo and Millonas, 1995) and (Santana and Correia, 2010) facilitates the cross-fertilisation between the study of collective and individual cognition through a common currency: stigmergy.

#### 5 Stigmergy within the living organism

In this section we look into studies highlighting stigmergic processes that occur internally to living organisms. As previously mentioned a living organism may be considered as a self-organized society of systems, which are themselves self-organized collectives of cells, not to mention that the cell itself may be analysed in that perspective as Tabony (2006) does regarding microtubules.

Besides this reference the term stigmergy is not used in any publication to qualify intra-organism coordination, although it was once used by Merks (2013) in a seminar presentation. Heylighen (2015) briefly mentions communication of internal organs through hormones in the bloodstream, however this is presented as the possibility of an individual using an internal medium in addition to the external medium in a stigmergic process of social organization.

In that work, the organism of a living being is not considered as a collective of agents that self-organize using stigmergy as one of the resources. However, we find different cases of self-organization internal to an organism where stigmergy plays an important role. For instance, stem cells reside in a specific environment denominated *niche* in which the extracellular matrix (ECM) both influences stem cell behavior and is influenced by it (Gattazzo et al, 2014) and (Merks, 2015). This is clearly a form of stigmergy. The interaction of cell membranes with other cells through the chemical media is another example (Schmick and Bastiaens, 2014).

In this work our main focus is to show the importance of stigmergy in the brain and neural cells in general, and the way it may play a fundamental role in the formation of cognition. The remaining of this section describes the main neuronal chemical and electrical stigmergic processes.

#### 5.1 Stigmergy in the brain

#### Neurotransmitters and Neuromodulators

Stigmergy being a coordination mechanism, in which an action left in a medium stimulates the performance of a subsequent action, it becomes evident that it encompasses the mechanisms of neuronal control. Thus, if the process of neuronal activity is taken as the action, the coordinated mechanism through which this action is controlled by substances (traces) that are released to the extracellular space (medium) to control subsequent neuronal activity (subsequent action), is tantamount to stigmergy.

Neuronal firing leads to the release of neurotransmitters, which are the molecules that are engaged in the transfer of information from one neuron to the next one in the network. Neuromodulators are molecules that are released together with the neurotransmitters, or as a consequence of neurotransmitter action. The function of the neuromodulators is to control the release of the neurotransmitters or their action, and in such a way, fine-tune neuronal activity. Neuromodulators can be released from the neurons or from nearby cells, as glial cells. There are several types of glial cells, with different functions in the nervous system, but all of them control neuronal activity and do so through the action of substances released into the extracellular space, this release being influenced by neuronal activity (Araque et al, 2014) and (Bezzi and Volterra, 2001). The different subtypes of glial cells include astrocytes, oligodendrocytes and microglia.

The understanding that a process from an astrocyte can wrap the nerve terminal and the postsynaptic zone to control synaptic activity gave rise, by the turn of the millennium (Araque et al, 1999) to the concept of tripartite synapse. Astrocytes respond to the neurotransmitters and neuromodulators released from neurons by releasing other neuromodulators that then act back into the pre- or the post-synaptic neuron, modulating their activity. Astrocytes themselves, once activated, change the activity of nearby astrocytes, which in turn can affect the activity of more distant neurons.

Microglia are another class of glial cells that also respond to neuronal activity and influence it (Erny et al, 2016), (Pierre et al, 2016) and (Ransohoff, 2016). They have predominantly a neuroimmune role, that is to say surveillance functions, they send alarm signals in case of neuronal injury or infection, and react helping to correct those dysfunctions, though in some cases, by overreacting may act as an aggravating factor. Dysfunctional neuroinflammation is one of a consequence of such overreaction.

Oligodendrocytes constitute a third class of glial cells, which crucially affect neuronal activity. They are responsible for the formation of myelin, which speeds the velocity of communication between distant parts of a neuron, thus speeding up information flow in the network, which may impact in network synchronization and thus into complex information processing tasks that involve coupling and synchrony among different brain rhythms (Pajevic et al, 2014). Interestingly, neuronal activity enhances the formation of myelin by oligodendrocytes (Fields, 2015) and does so through molecules that are released by neurons during neuronal activity, which act in oligodendrocytes to enhance their ability to myelinate specific areas of the neuron. Again, this can be considered as an example of stigmergy.

All the mechanisms identified above, involve the release of neuromodulators by neurons or glial cells, which then act in the neurons (and in glia cells) to modify their biological activity, including the neuronal firing properties as well as the amount of neurotransmitter released, or the efficiency of the action of the neurotransmitter at the postsynaptic neuron, or even the time the neurotransmitter stays at the synapse, that is to say, its reuptake by neurons or glial cells. Frequently, if not always, neuromodulators are released as a function of neuronal activity. Some neuromodulators act as negative-feedback traces, contributing to keep the gain of the network at a relatively constant level, some others act as positive feedback traces, reinforcing neuronal activity under high neuronal output conditions, thus subserving processes of activity induced synaptic reinforcement. A common characteristic of the neuromodulators is that they act at short distances, affecting neurons and synapses located close (i.e., a few cells apart) to their release sites. Their action occurs within a time frame of milliseconds to seconds. A well known example of neuromodulador is adenosine (Dias et al, 2013), (Sebastião and Ribeiro, 2015) and (Rombo et al, 2016), whose membrane receptors are the targets of caffeine (Ribeiro and Sebastião, 2010). Other well known examples are endocannabinoids (Katona and Freund, 2012), whose membrane receptors are the targets of cannabis (Solymosi and Köfalvi, 2016).

Other group of modulators of neuronal activity are the neurohormones.<sup>5</sup> This is the case of the hormones released at the level of the hypothalamus that travel a short distance to affect the activity of the hypophysis, an endocrine gland that in turn releases other hormones into the circulation that, by travelling throughout the body, affect in turn the release of other hormones by target organs that entering into circulation feedback to influence neuronal activity. This is the case of sex hormones, stress hormones, among others. In contrast to neuromodulators, the action of hormones is long lasting either in space or in time. In common to neuromodulators, they can be regarded as traces that act through the medium to affect the activity of an agent that contributed to their action, and thus they also operate stigmergy. This happens also at a macroscopic scale: "It also has been demonstrated that hormones may affect behavior and in turn may be affected by emotions" (Emerson, 1968).<sup>6</sup>

#### Electrical signals

At a smaller timescale than that of neurotransmitters and neuromodulators we find stigmergy supported by electric signals. It is not the direct electrical connection among neurons that supports it, but a global, at the space scale of the whole brain, communication through propagating electrical waves (Schnitzler and Gross, 2005) and (Buzsáki and Schomburg, 2015). Fries (2005) names this process as "neuronal communication through neuronal coherence".

Neuronal groups oscillations influence the instant of single neuron spike output, and therefore this process can be seen as an indirect communication among neurons. In particular synchronisation seems to benefit communication among groups of neurons, which is specially evident in oscillatory signals. This is a clear case of stigmergy. Individual neuron spikes synchronize in a group of neurons producing a "global" signal (detected by EEC) which, in turn, influences other neurons. The persistence of the signal can be associated with the duration of the periodic signal (wave). The possibility of gamma synchrony being correlated to consciousness (Brancucci, 2012) also substantiates the idea that stigmergy at neuronal level is a support for the formation of cognition.

#### 6 Conclusion

The emergence of collective cognition is ascribed to stigmergic processes in a variety of societies. The fact that this phenomenon is found within individuals, namely in the neural system, has been highlighted for the first time in this article. We have described several concurrent stigmergic processes in the body and in particular in the brain, which play a significant role for the formation of cognition of the individual. As a matter of fact, stigmergy can be seen as a unifying concept of intra-individual emergence of mental states, and interindividual emergence of culture.

In swarm cognition, an agent, either a living being or a neuron, does not know to the complete state of the system. It may have access to global variables, representing part of the state, but it can not get the states of all other similar agents. Stigmergy seems to be a very adequate way to bridge local and global spatiotemporal patterns that form cognitive concepts. Like cognition, it is a self-organized process. However, stigmergy is a particular form of self-organization and therefore it provides a simplified process to the cognitive functions it supports.

In section 4 we have described some of the first models making use of stigmergy in cognitive functions

 $<sup>^5</sup>$  see for instance (Garcia-Segura and Nicola, 2011) for a series of articles on the activity of several hormones in the brain.

<sup>&</sup>lt;sup>6</sup> a slightly updated version of (Emerson, 1954).

of artificial devices. The main advantages of such approaches are the implementation of active and sparse spacial memories, the robustness, specially evident in a good speed-accuracy trade-off, and a common currency to study cognition across scales, from the individual to the society.

With this work we hope to motivate for further research in artificial intelligence exploring the formation of cognition, inspired in the variety of stimergic processes in the brain, described in section 5. Several aspects are yet to be studied, such as the extent of cognitive processes that need a significant support by stigmergy, or the relation of global variables to specific cognitive concepts, or the articulation between direct and indirect (stigmergic) communication. Altogether, in the study of a concept as complex as cognition it seems unwise to overlook such an amount of evidence showing that stigmergy necessarily plays a relevant role in it.

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