

Bio-inspired Communication for Self-regulated Multi-robot Systems

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1. Introduction

In recent years, the study of biological social insects and other animals reveals us that simple individuals of these self-organized societies can solve various complex and large everyday-problems with a few behavioural rules (Camazine et al., 2001). In these self-organized systems, an individual agent may have limited cognitive, sensing and communication capabilities. But they are collectively capable of solving complex and large problems, e.g. coordinated nest construction of honey-bees, collective defence of school fishes from a predator attack, ordered homing of bats. Since the discovery of these collective behavioural patterns of self-organized societies, scientists observed modulation or adaptation of behaviours in the individual level (Garnier et al., 2007). One of the most notable such self-regulatory processes in biological social systems is the *division of labour* (DOL) (Sendova-Franks & Franks, 1999) by which a larger task is divided into a number of small subtasks and each subtask is performed by a separate individual or a group of individuals.

From the study of social insects and other biological societies, we can find that two major metrics of DOL have been established in literature.

Task-specialization. *Task-specialization* is an integral part of DOL where a worker usually does not perform all tasks, but rather specializes in a set of tasks, according to its morphology, age, or chance (Bonabeau et al., 1999). This DOL among nest-mates, whereby different activities are performed simultaneously by groups of specialized individuals, is believed to be more efficient than if tasks are performed sequentially by unspecialised individuals.

Plasticity. DOL is also characterized by *plasticity* which means that the removal of one class of workers is quickly compensated for by other workers. Thus distributions of workers among different concurrent tasks keep changing according to the external (environmental) and internal conditions of a colony (Garnier et al., 2007).

In artificial social systems, like multi-agent or multi-robot system, the term “division of labour” is often found synonymous to “task-allocation” (Shen et al., 2001). In robotics, this is called *multi-robot task allocation* (MRTA) which is generally identified as the question of assigning tasks in an appropriate time to the appropriate robots considering the changes of the environment and/or the performance of other team members (Gerkey & Mataric, 2004). In this chapter, we have presented this issue of DOL as the representative self-regulatory process in both biological and artificial social systems. We have used the terms DOL and MRTA (or simply, task-allocation) interchangeably.

The complexities of the distributed MRTA problem arise from the fact that there is no central planner or coordinator for task assignments, and in a large multi-robot systems, generally robots have limited capabilities to sense, to communicate and to interact locally.

Traditionally, task allocation in a multi-agent systems has been divided into the following two major categories.

Predefined task-allocation. Early research on predefined task-allocation was dominated by intentional coordination (Parker, 2008), use of dynamic role assignment (Chaimowicz et al., 2002) and market-based bidding approach (Dias et al., 2006). Under these approaches, robots use direct task-allocation method, often to communicate with group members for negotiating on tasks. These approaches are intuitive, comparatively straight forward to design and implement and can be analysed formally. However, these approaches typically works well only when the number of robots are small (≤ 10) (Lerman et al., 2006).

Bio-inspired self-organized task-allocation. This approach relies on the emergent group behaviours, such as emergent cooperation (Kube & Zhang, 1993), adaptation rules (Liu et al., 2007) etc. They are more robust and scalable to large team sizes. However, most of the robotic researchers found that self-organized task-allocation approach is difficult to design, to analyse (formally) and to implement in real robots.

Within the context of the Engineering and Physical Sciences Research Council (EPSRC) project, "Defying the Rules: How Self-regulatory Systems Work", we have proposed to solve the above mentioned self-regulated DOL problem in an alternate way (Arcaute et al., 2008). Our approach is inspired from the studies of emergence of task-allocation in both biological and human social systems in which we have found that a large number of species grow, evolve and generally continue functioning well by the virtue of their individual self-regulatory DOL systems. It is interesting to note that in self-regulated societies, task-allocation has been accomplished years after years without a central authority or an explicit planning and coordinating element. Direct and indirect communication strategies are used to exchange information among individuals (Camazine et al., 2001).

From our multi-disciplinary studies of various self-regulated systems, we have proposed four generic rules to explain self-regulation in those social systems. These four rules are: *continuous flow of information, concurrency, learning and forgetting*, all of them will be explained later. Primarily these rules deal with the issue of deriving local control laws for regulating an individual's task-allocation behaviour that can facilitate the DOL in the entire group. In order employ these rules in the individual level, we have developed a formal model of self-regulated DOL, called the attractive field model (AFM). AFM provides an abstract framework for self-regulatory DOL in social systems.

In biological social systems, communications among the group members, as well as sensing the task-in-progress, are two key components of self-organized DOL. In robotics, existing self-organized task-allocation methods rely heavily upon local sensing and local communication of individuals for achieving self-organized task-allocation. However, AFM differs significantly in this point by avoiding the strong dependence on the local communications and interactions found in many existing approaches to MRTA. AFM requires a system-wide continuous flow of information about tasks, agent states etc. but this can be achieved by using both centralized and decentralized communication modes under explicit and implicit communication strategies.

In order to enable continuous flow of information in our multi-robot system, we have implemented two types of sensing and communication strategies inspired by the self-regulated

DOL found in two types of social wasps: *polistes* and *polybia* (Jeanne, 1999). Depending on the group size, these species follow different strategies for communication and sensing of tasks. *Polistes* wasps are called the *independent founders* in which reproductive females establish colonies alone or in small groups (in the order of 10^2), but independent of any sterile workers. On the other hand, *polybia* wasps are called the *swarm founders* where a swarm of workers and queens initiate colonies consisting of several hundreds to millions of individuals. The most notable difference in the organization of work of these two social wasps is: independent founders do not rely on any cooperative task performance while swarm founders interact with each-other locally to accomplish their tasks. The work mode of independent founders can be considered as *global sensing - no communication (GSNC)* where the individuals sense the task requirements throughout a small colony and do these tasks without communicating with each other. On the other hand, the work mode of swarm founders can be treated as *local sensing - local communication (LSLC)* where the individuals can only sense tasks locally due to large colony-size and they can communicate locally to exchange information, e.g. task-requirements (although their exact mechanism is unknown). In this chapter, we have used these two sensing and communication strategies to compare the performance of the self-regulated DOL of our robots under AFM.

2. The Attractive Field Model (AFM)

2.1 Generic framework

Inspired from the DOL in ants, humans and robots, we have proposed the following four *generic rules of self-regulation*.

Rule 1: Continuous flow of information. Self-regulatory social systems establish the continuous minimum flow of information over the period of time when self-regulation can be defined. This should help to maintain at least two states of an agent: 1) receiving information about task(s) and 2) ignoring information or doing no task. The up-to-date information should reflect the changes of the system i.e. it should encode the necessary feedback for the agents. Thus, this property will act as the basis of the state switching of agents, between these two minimum states or, among multiple states e.g. in case of multiple tasks or many sub-states of a single task.

At the individual level, information is processed differently by each individual, and is certainly not constant nor continuous. The time scale at the individual level is very small compared to the system level's time scale. We can approximate the propagation of information at this macro time scale as the continuous flow of information. In the model, emphasis is given to whether the information is used e.g. stimulation to perform a task, or unused e.g. random walk.

Rule 2: Sensitization. Self-regulatory social systems allow the differentiation in the use of (or access to) information, e.g. through sensitization or learning of some tasks. This differentiation is regulated by the characteristics of the system, e.g. the ability of the agents to learn tasks that are repeatedly performed.

Rule 3: Concurrence. Self-regulatory social systems include concurrent access to information from different spatial locations with certain preferences. This preference is not fixed and can change with the dynamics of the system.

Rule 4: Forgetting. Self-regulatory social systems include forgetting, e.g. the ability of the agents to diminish information over time, if not used. The system determines the amount of information being released, and this may change over time. For example, specialists might

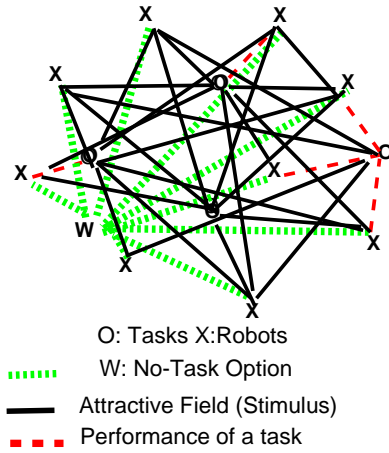


Figure 1. The attractive filed model (AFM)

have to attend an emergency situation and switch tasks that contributes to the forgetting of old task experiences. This is considered as crucial to allow flexibility in the system.

Having this general framework of self-regulatory social systems, we can now formalize AFM that will describe the properties of individual agents and the system as a whole. In terms of networks, the model is a bipartite network, i.e. there are two different types of nodes. One set of nodes describes the sources of the attractive fields and the other set describes the agents. Links only exist between different types of nodes and they encode the flow of information so that, even if there is no direct link between two agents, their interaction is taken into account in the information flow. This is an instance of *weak* interaction. The strength of the field primarily depends upon the distance between the task and the agent. This relationship is represented using weighted links. Besides, there is a permanent field that represents the *no-task* or option for ignoring information. The model can be mapped to a network as shown in Fig. 1. The correspondence is given below:

1. Source nodes (o) are tasks that can be divided between a number of agents.
2. Agent nodes (x) can be ants, human, robots etc.
3. The attractive fields correspond to stimuli to perform a task, and these are given by the black solid lines.
4. When an agent performs a task, the link becomes different, and this is denoted in the figure by a dashed line. Agents linked to a source by a red line are the agents currently doing that task.
5. The field of ignoring the information (w) corresponds to the stimulus to random walk, i.e. the no-task option, and this is denoted by the dotted lines in the graph.
6. Each of the links is weighted. The value of this weight describes the strength of the stimulus that the agent experiences. In a spatial representation of the model, it is easy to see that the strength of the field depends on the physical distance of the agent to the source. Moreover, the strength can be increased through sensitisation of the agent via experience (learning). This distance is not depicted in the network, it is represented

through the weights of the links. In the figure of the network (Fig. 1), the nodes have arbitrary places. Note that even though the distance is physical in this case, the distance in the model applied to other systems, needs not to be physical. It can represent the accessibility to the information, the time the information takes to reach the receiver, etc.

In summary, from the above diagram of the network, we can see that each of the agents is connected to each of the fields. This means that even if an agent is currently involved in a task, the probability that it stops doing it in order to pursue a different task, or to random walk, is always non-zero. The weighted links express the probability of an agent to be attracted to each of the fields.

2.2 Interpretation of AFM in multi-robot systems

The interpretation of AFM in a multi-robot system follows the above mentioned generic interpretation. Let us consider a multi-tasking environment, where N number of autonomous mobile robots are required to attend J number of tasks spread over a fixed area A .

Let a task j has an associated task-urgency ϕ_j indicating its relative importance over time. If a robot attends a task j in the x^{th} time-step, the value of ϕ_j will decrease by an amount $\delta_{\phi_{INC}}$ in the $(x + 1)^{th}$ time-step. On the other hand, if a task has not been served by any robot in the x^{th} time-step, ϕ_j will increase by another amount $\delta_{\phi_{DEC}}$ in $(x + 1)^{th}$ time-step. Thus urgency of a task is updated by the following rules.

$$\text{If the task is not being done : } \phi_j \rightarrow \phi_j + \delta_{\phi_{INC}} \quad (1)$$

$$\text{If the task is being done : } \phi_j \rightarrow \phi_j - n \delta_{\phi_{DEC}} \quad (2)$$

Eq. 1 refers to a case where no robot attend to task j and Eq. 2 refers to another case where n robots are concurrently performing the task j .

In order to complete a task j , a robot r_i needs to be within a fixed boundary D_j . If a robot completes a task j it learns about it and this will influence r_i 's likelihood of selecting that task in future, say through increasing its sensitization to j by a small amount, k_{INC} . Here, the variable affinity of a robot r_i to task j is called as its *sensitization* k_j^i . If a robot i does not do a task j for some time, it forgets about j and k_j^i is decreased, by another small amount, say k_{DEC} . Thus a robot's task-sensitization is updated by following these rules.

$$\text{If task is done : } k_j^i \rightarrow k_j^i + k_{INC} \quad (3)$$

$$\text{If task is not done : } k_j^i \rightarrow k_j^i - k_{DEC} \quad (4)$$

According to AFM, all robots will establish attractive fields to all tasks due to the presence of a system-wide continuous flow of information. The strength of these attractive fields will vary according to the dynamic distances between the robots and tasks, task-urgencies and corresponding sensitizations of robots. Simplifying the generic implementation of AFM from Arcaute et al. (2008), we can formally encode this stimuli of attractive field as follows.

$$S_j^i = \tanh\left\{\frac{k_j^i}{d_{ij} + \delta} \phi_j\right\} \quad (5)$$

$$S_{RW}^i = \tanh\left\{1 - \frac{\sum_{j=1}^J S_j^i}{J + 1}\right\} \quad (6)$$

Table 1. Common communication modalities in biological social systems

Modality	Range	Information type
Sound	Long ^a	Advertising about food source, danger etc.
Vision	Short ^b	Private, e.g. courtship display.
Chemical	Short/long	Various messages, e.g. food location, alarm etc.
Tactile	Short	Qualitative info, e.g. quality of flower, peer identification etc.
Electric	Short/long	Mostly advertising types, e.g. aggression messages.

^a Depending on the type of species, long range signals can reach from a few metres to several kilometres.

^b Short range typically covers from few mm to about a metre or so.

$$P_j^i = \frac{S_j^i}{\sum_{j=0}^J S_j^i} \quad \text{where, } S_0^i = S_{RW}^i \quad (7)$$

Eq. 5 states that the stimuli of a robot r_i to a particular task j , S_j^i depends on r_i 's spatial distance to j (d_{ij}), level of sensitization to j (k_j^i), and perceived urgency of that task (ϕ_j). In Eq. 5, we have used a very small constant value δ , called *delta distance*, to avoid division by zero, in the case when a robot has reached to a task. Since S_j^i is a probability function, it is chosen as a *tanh* in order to keep the values between 0 and 1. Eq. 6 suggests us how we can estimate the stimuli of random walk or no-task option. This stimuli of random walk depends on the sum of stimulus of J real tasks. Here, random-walk is also considered as a task. Thus the total number of tasks become $J + 1$. The probability of selecting each task has been determined by a probabilistic method outlined in Eq. 7 which states that the probability of choosing a task j by robot r_i is directly proportional to its calculated stimuli S_j^i .

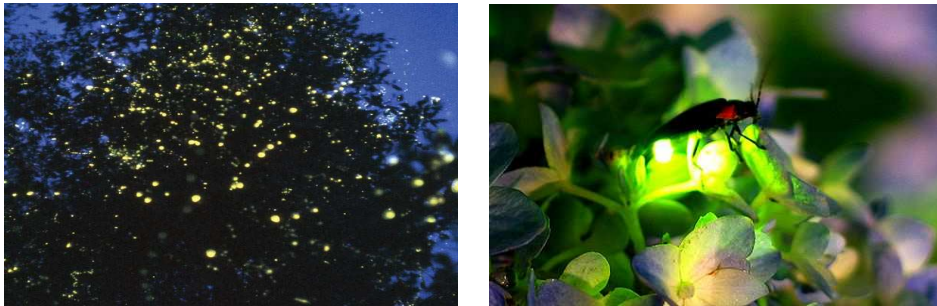
3. Communication in biological social systems

Communication plays a central role in self-regulated DOL of biological social systems. In this section, communication among social insects are briefly reviewed.

3.1 Purposes, modalities and ranges

Communication in biological societies serves many closely related social purposes. Most P2P communication include: recruitment to a new food source or nest site, exchange of food particles, recognition of individuals, simple attraction, grooming, sexual communication etc. In addition to that colony-level broadcast communication include: alarm signal, territorial and home range signals and nest markers, communication for achieving certain group effect such as, facilitating or inhibiting a group activity (Holldobler & Wilson, 1990).

Biological social insects use different modalities to establish social communication, such as, sound, vision, chemical, tactile, electric and so forth (Table 1). Sound waves can travel a long distance and thus they are suitable for advertising signals. They are also best for transmitting complicated information quickly (Slater, 1986). Visual signals can travel more rapidly than sound, but they are limited by the physical size or line of sight of an animal. They also do not travel around obstacles. Thus they are suitable for short-distance private signals.



(a) Flashing fireflies

Figure 2. (a) Flashing lights of fireflies displaying their synchronous behaviours (b) A firefly can produce light to signal other fireflies.

From <http://www.letsjapan.markmode.com>, last seen on 01/06/2010.

In ants and some other social insects, chemical communication is predominant. Any kind of chemical substance that is used for communication between intra-species or inter-species is termed as *semiochemical* (Holldobler & Wilson, 1990). A pheromone is a semiochemical, usually a type of glandular secretion, used for communication within species. One individual releases it as a signal and others respond to it after tasting or smelling. Using pheromones individuals can code quite complicated messages in smells. For example, a typical ant colony operates with somewhere between 10 and 20 kinds of signals. Most of these are chemical in nature. If wind and other conditions are favourable, this type of signals emitted by such a tiny species can be detected from several kilometres away. Thus chemical signals are extremely economical of their production and transmission. But they are quite slow to diffuse away. But ants and other social insects manage to create sequential and compound messages either by a graded reaction of different concentrations of same substance or by blends of signals.

Tactile communication is also widely observed in ants and other species typically by using their body antennae and forelegs. It is observed that in ants touch is primarily used for receiving information rather than informing something. It is usually found as an invitation behaviour in worker recruitment process. When an ant intends to recruit a nest-mate for foraging or other tasks it runs upto a nest-mate and beats her body very lightly with antennae and forelegs. The recruiter then runs to a recently laid pheromone trail or lays a new one. In this form of communication limited amount of information is exchanged. In underwater environment some fishes and other species also communicate through electric signals where their nerves and muscles work as batteries. They use continuous or intermittent pulses with different frequencies to learn about environment and to convey their identity and aggression messages.

3.2 Signal active space and locality

The concept of active space (AS) is widely used to describe the propagation of signals by species. In a network environment of signal emitters and receivers, active space is defined as the area encompassed by the signal during the course of transmission (McGregor & Peake, 2000). In case of long-range signals, or even in case of short-range signals, this area include several individuals where their social grouping allows them to stay in cohesion. The concept

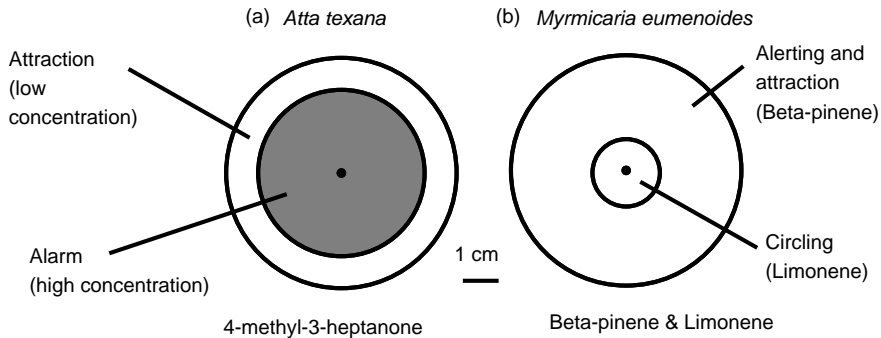


Figure 3. Pheromone active space observed in ants, reproduced from Holldobler & Wilson (1990).

of active space is described somewhat differently in case some social insects. In case of ants, this active space is defined as a zone within which the concentration of pheromone (or any other behaviourally active chemical substances) is at or above threshold concentration (Holldobler & Wilson, 1990). Mathematically this is denoted by a ratio:

$$AS = \frac{\text{Amount of pheromone emitted } (Q)}{\text{Threshold concentration at which the receiving ant responds } (K)} \quad (8)$$

Here, Q is measured in number of molecules released in a burst or in per unit of time whereas K is measured in molecules per unit of volume. Fig. 3 shows the use of active spaces of two species of ants: (a) *Atta texana* and (b) *Myrmicaria eumenoides*. The former one uses two different concentrations of 4-methyl-3-heptanone to create attraction and alarm signals, whereas the latter one uses two different chemicals: *Beta-pinene* and *Limonene* to create similar kinds signals, i.e. alerting and circling.

The adjustment of this ratio enables individuals to gain a shorter fade-out time and permits signals to be more sharply pinpointed in time and space by the receivers. In order to transmit the location of the animal in the signal, the rate of information transfer can be increased by either lowering the rate of emission of Q or by increasing K , or both. For alarm and trail systems a lower value of this ratio is used. Thus, according to need, individuals regulate their active space by making it large or small, or by reaching their maximum radius quickly or slowly, or by enduring briefly or for a long period of time. For example, in case of alarm, recruitment and sexual communication signals where encoding the location of an individual is needed, the information in each signal increases as the logarithm of the square of distance over which the signal travels. From the precise study of pheromones it has been found that active space of alarm signal is consists of a concentric pair of hemispheres (Fig. 3). As an ant enters the outer zone, she is attracted inward toward the point source; when she next crosses into the central hemisphere she become alarmed. It is also observed that ants can release pheromones with different active spaces.

Active space has strong role in modulating the behaviours of ants. For example, when workers of *Acanthomyops claviger* ants produce alarm signal due to an attack by a rival or insect predator, workers sitting a few millimetres away begin to react within seconds. However, those ants sitting a few centimetres away take a minute or longer to react. In many cases, ants and other



Figure 4. A group of ants following pheromone-trail.
From <http://www.bioteams.com>, last seen on 01/06/2010.



Figure 5. A dancing honey-bee (centre) and its followers.
From <http://knol.google.com>, last seen on 01/06/2010.

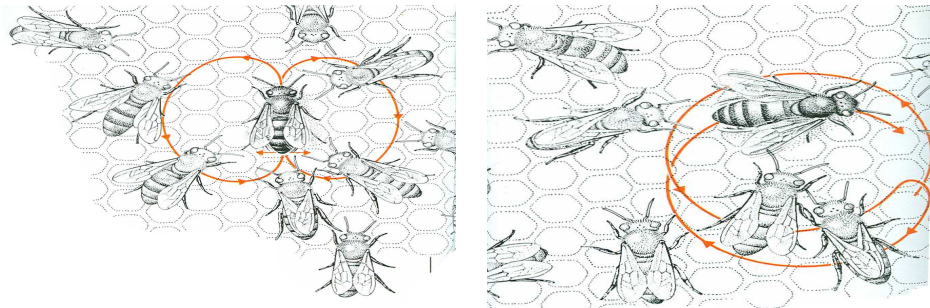
Table 2. Common communication strategies in biological social systems

Communication strategy	Common modalities used
Indirect	Chemical and electric
P2P	Vision and tactile
Local broadcast	Sound, chemical and vision
Global broadcast	Sound, chemical and electric

social insects exhibit modulatory communication within their active space where many individuals involve in many different tasks. For example, while retrieving the large prey, workers of *Aphaenogaster* ants produce chirping sounds (known as *stridulate*) along with releasing poison gland pheromones. These sounds attract more workers and keep them within the vicinity of the dead prey to protect it from their competitors. This communication amplification behaviour can increase the active space to a maximum distance of 2 meters.

3.3 Common communication strategies

In biological social systems, we can find all different sorts of communication strategies ranging from indirect pheromone trail laying to local and global broadcast of various signals. Sec. ?? discusses the most common four communication strategies in natural and artificial world, i.e. indirect, P2P, local and global broadcast communication strategies. Table 2 lists the use of various communication modalities under different communication strategies. Here we give a few real examples of those strategies from biological social systems. In biological literature, the pheromone trail laying is one of the most discussed indirect communication strategy among various species of ants. Fig. 4 shows a pheromone trail following of a group of foraging ants. This indirect communication strategy effectively helps ants to find a better food source among multiple sources, find shorter distance to a food source, marking nest site and move there etc. (Hughes, 2008). Direct P2P communication strategy is also very common among most of the biological species. Fig. 7 shows P2P communication of ants and honey-bees. This tactile form



(a) Honey-bee's waggle dance

Figure 6. Examples of local broadcast communication of honey-bees: (a) Honey-bees show waggle-dance (making figure of 8) when food is far and (b) they show round-dance without any waggle when food is closer (within about 75m of hive). From Slater (1986).



(a) Two honey-bees

Figure 7. Example of P2P tactile communication: (a) Honey-bees exchange nectar samples by close contact (b) ants also exchange food or information via tactile communication. From <http://www.harunyahya.com/> last seen 01/05/2010.

of communication is very effective to exchange food item, flower nectar with each-other or this can be useful even in recruiting nest-mates to a new food source or nest-site.

3.4 Roles of communication in task-allocation

Communication among nest-mates and sensing of tasks are the integral parts of the self-regulated DOL process in biological social systems. They create necessary preconditions for switching from one tasks to another or to attend dynamic urgent tasks. Suitable communication strategies favour individuals to select a better tasks. For example, Garnier et al. (2007) reported two worker-recruitment experiments on black garden ants and honey-bees. The scout ants of *Lasius niger* recruit uninformed ants to food source using a well-laid pheromone trails. *Apis mellifera* honey-bees also recruit nest-mates to newly discovered distant flower sources through waggle-dances. In the experiments, poor food sources were given first to both ants and honey-bees. After some time, rich food sources were introduced to them. It was found

Table 3. Self-regulation of communication behaviours in biological social systems

Example event	Strategy	Modulation of communication upon sensing tasks
Ant's alarm signal by pheromones	Global broadcast	High concentration of pheromones increase aggressive alarm-behaviours
Honey-bee's round dance	Local broadcast	High quality of nectar source increases dancing and foraging bees
Ant's tandem run for nest selection	P2P	High quality of nest increases traffic flow
Ant's pheromone trail-laying to food sources	Indirect	Food source located at shorter distance gets higher priority as less pheromone evaporates and more ants joins

that only honey-bees were able to switch from poor source to a rich source using their sophisticated dance communication.

Table 3 presents the link between sensing the task and self-regulation of communication behaviours among ants and honey-bees. Here, we can see that communication is modulated based on the perception of task-urgency irrespective of the communication strategy of a particular species. Under indirect communication strategy of ants, i.e. pheromone trail-laying, we can see that the principles of self-organization, e.g. positive and negative feedbacks take place due to the presence of different amount of pheromones for different time periods. Initially, food source located at shorter distance gets relatively more ants as the ants take less time to return nest. So, more pheromone deposits can be found in this path as a result of positive feedback process. Thus, the density of pheromones or the strength of indirect communication link reinforces ants to follow this particular trail.

Similarly, perception of task-urgency influences the P2P and broadcast communication strategies. *Leptothorax albipennis* ant take less time in assessing a relatively better nest site and quickly return home to recruit its nest-mates (Pratt et al., 2002). Here, the quality of nest directly influences its intent to make more "tandem-runs" or to do tactile communication with nest-mates. We have already discussed about the influences of the quality of flower sources to honey-bee dance. Fig. 8 shows this phenomena more vividly. It has been plotted using the data from the honey-bee round-dance experiments of (Von Frisch, 1967, p. 45). In this plot, Y1 line refers to the concentration of sugar solution. This solution was kept in a bowl to attract honey-bees and the amount of this solution was varied from $\frac{3}{16}$ M to 2M (taken as 100%). In this experiment, the variation of this control parameter influenced honey-bees' communication behaviours while producing an excellent self-regulated DOL.

In Fig. 8 Y2 line represents the number of collector bees that return home. The total number of collectors was 55 (taken as 100%). Y3 line plots the percent of collectors displaying round dances. We can see that the fraction of dancing collectors is directly proportional to the concentration of sugar solution or the sensing of task-urgency. Similarly, the average duration of dance per bee is plotted in Y4 line. The maximum dancing period was 23.8s (taken as 100%). Finally, from Y5 line we can see the outcome of the round-dance communication as the number of newly recruited bees to the feeding place. The maximum number of recruited bees was 18 (taken as 100%). So, from an overall observation, we can see that bees

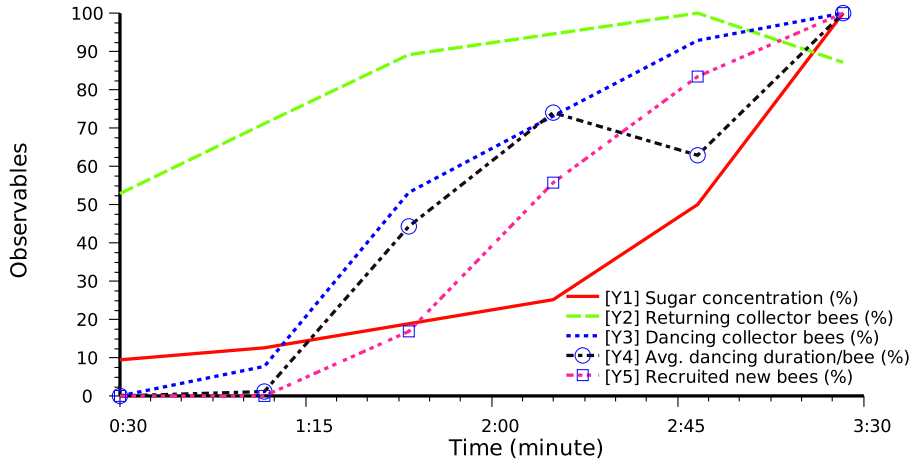


Figure 8. Self-regulation in honey-bee's dance communication behaviours, produced after the results of Von Frisch (1967) honey-bee round-dance experiment performed on 24 August 1962.

sense the concentration of food-source as the task-urgency and they self-regulate their round-dance communication behaviour according to their perception of this task-urgency. Thus, this self-regulated dancing behaviour of honey-bees attracts an optimal number of inactive bees to work.

Broadcast communication is one of the classic ways to handle dynamic and urgent tasks in biological social systems. It can be commonly observed in birds, ants, bees and many other species. Table 3 mentions about the alarm communication of ants. Similar to the honey-bee's dance communication, ants has a rich language of chemical communication that can produce words through blending of different glandular secretions in different concentrations. Fig. 3 shows how ants can use different concentrations of chemicals to make different stimulus for other ants. From the study of ants, it is clear to us that taking defensive actions, upon sensing a danger, is one of the highest-priority tasks in an ant colony. Thus, for this highly urgent task, ants almost always use their global broadcast communication strategy through their strong chemical signals and they make sure all individuals can hear about this task. This gives us a coherent picture of the self-regulation of biological species based on their perception of task-urgency.

3.5 Effect of group size on communication

The performance of cooperative tasks in large group of individuals also depends on the communication and sensing strategies adopted by the group. As introduced in Sec. ??, from the study of social wasps, we can find that depending on the group size, different kinds of information flow occur in different types of social wasps (Jeanne, 1999). *Polistes* independent founders (Fig. 9(a)) are species in which reproductive females establish colonies alone or in small groups with about 10^2 individuals at maturity. *Polybia* swarm founders (Fig. 9(b)) initiates colonies by swarm of workers and queens. They have a large number of individuals, in the order of 10^6 and 20% of them can be queen. Fig. 10 compares the occurrence of information flow among independent and swarm founders. In case of swarm founders information about nest-construction or broods food-demand can not reach to foragers directly. Fig. 11



(a) Socail wasps

Figure 9. Colony founding in two types of social wasps (a) *Polistes* founds colony by a few queens independently (b) *Polybia occidentalis* founds colony by swarms. From <http://www.discoverlife.org>, last seen 01/05/2010.

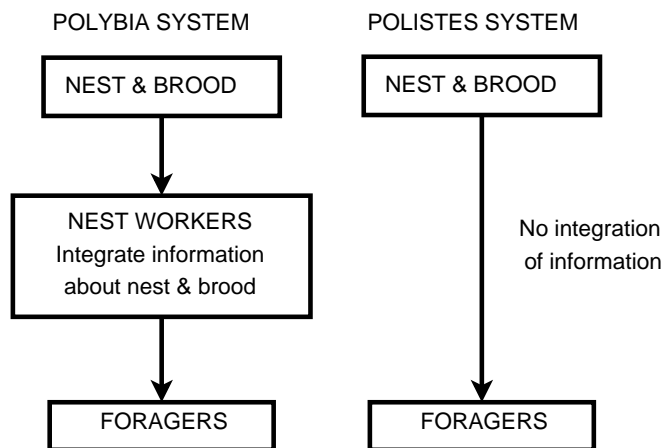


Figure 10. Different patterns of information flow in two types of social wasps: polybia and polistes, reproduced from Jeanne (1999).

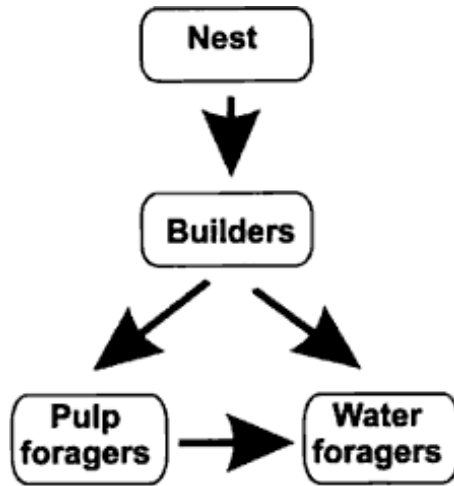


Figure 11. Information flow in polybia social wasps, reproduced from Jeanne (1999).

shows the path of information flow among swarm founders for nest construction. The works of *pulp foragers* and *water foragers* depend largely on their communication with *builders*. On the other hand, in case of independent founders there is no such communication and sensing are present among individuals. In Sec. ?? we have termed these two types communication and sensing strategies as GSNC (for independent founders) and LSLC (swarm founders).

Jeanne (1999) explained the above phenomena of selecting different strategies in terms of task-specialization patterns and stochastic properties found in the group. In case of large colonies, many individuals repeatedly performs same tasks as this minimizes their interferences, although they still have a little probability to select a different task randomly. But because of the large group size, the queuing delay in inter-task switching keeps this task-switching probability very low. Thus, in swarm founders, task-specialization becomes very high among individuals. On the other hand, in small group of independent founders, specialization on a specific task is very costly, because this prevents individuals not to do other tasks whose task-urgencies can soon become very high. Thus these individuals tend to become generalist and do not communicate task information with each other.

The above interesting findings on GSNC and LSLC in social wasps have been linked up with the group productivity of wasps. Fig. 12 illustrates high group productivity in case of LSLC of swarm founders. The per capita productivity was measured as the number of cells built in the nest in (a) and the weight of dry brood in grams in (b). In case of independent founders this productivity is much lesser (max. 24 cells per queen at the time the first offspring observed) comparing to the thousands of cells produced by swarm founders. This shows us the direct link between high productivity of social wasps and their selection of LSLC strategy. These fascinating findings from wasp colonies have motivated us to test these communication and sensing strategies in a fairly large multi-robot system to achieve an effective self-regulated MRTA.

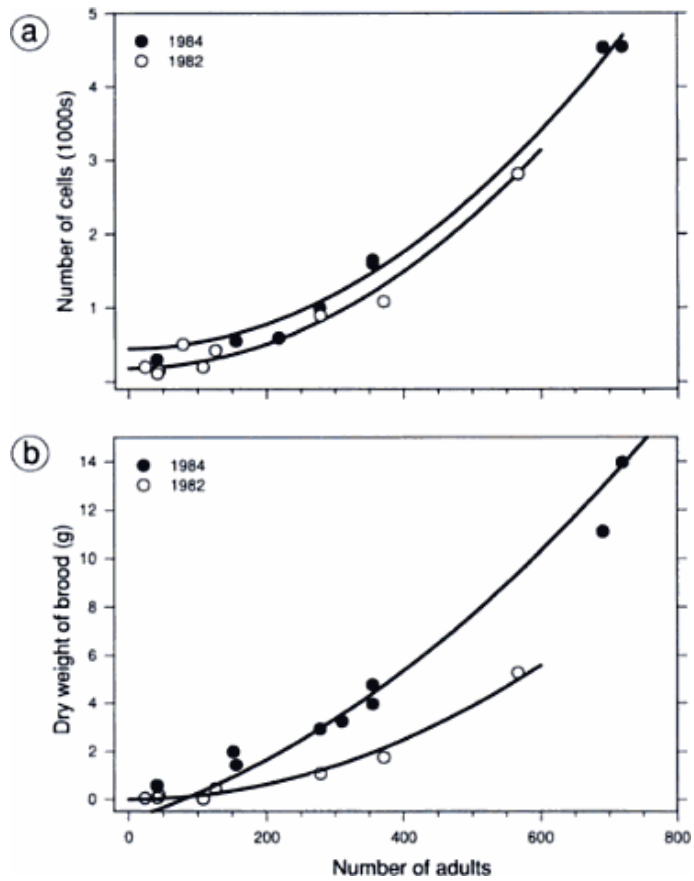


Figure 12. Productivity of social wasps shown as a function of group size, reproduced from Jeanne (1999).

4. Communication in multi-robot systems

Communication plays an important role for any high-level interaction (e.g. cooperative or coordinative) among a multi-robot team Arkin (1998). This is not a prerequisite for the group to be functioning, but often act as a useful component of multi-robot system. The characteristics of communication in multi-robot system can be presented in terms of these issues:

- Rationale of communication: *why do the robots communicate?*
- Message content: *what do they communicate?*
- Communication modalities: *How do they communicate?*
- Target recipients: *With whom do they communicate?*

Below we have described the above issues with a focus on how communication can lead to produce effective MRTA solutions.

4.1 Rationale of communication

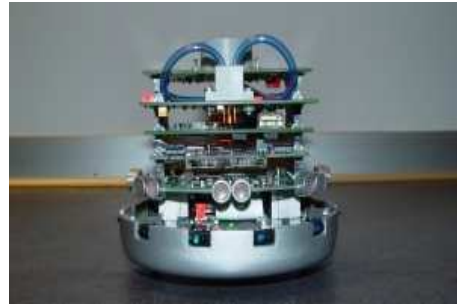
From three kinds of communication experiments: indirect stigmergic communication, direct robot-robot state communication, and goal communication, (Balch, 2005) found that in some tasks communication provided performance improvements while others did not. Most of the robotic researchers generally agree that communication in multi-robot system usually provides several major benefits listed below.

1. **Improved perception:** Robots can exchange potential information (as discussed below) based on their spatial position and knowledge of past events. This, in turn, leads to improve perception over a distributed region without directly sensing it.
2. **Synchronization of actions:** In order to perform (or stop performing) certain tasks simultaneously or in a particular order, robots need to communicate, or signal, to each other.
3. **Enabling interactions and negotiations:** Communication can help a lot to influence each-other in a team that, in turn, enables robots to interact and negotiate their actions effectively.

4.2 Information content

Although communication provides several benefits for team-work it is costly to provide communication support in terms of hardware, firmware as well as run-time energy spent in communication. So robotic researchers carefully minimize the necessary information content in communications by using suitable communication protocols and high-level abstractions. For example in foraging, grazing and consuming experiments, Balch & Arkin (1994) introduced state and goal communications. In state communication, a single bit is transmitted indicating the current state of robot (e.g. 0 transmitted when robot was in *Wander* state and 1 transmitted when robot was in *Acquire* or *Retrieve* states). In case of goal communication, the location of task was also transmitted. Here is a brief summary of potential information contents used in communication among robots.

- **Individual state:** ID number, battery level, task-performance statistics, e.g. number of tasks done.
- **Goal:** Location of target task or all tasks discovered.
- **Task-related state:** The amount of task completed, number of other robots present there etc.



(a) E-puck robots with table-lamps and Sniffing Khepera III

Figure 13. (a) A fleet of mobile “lighting” robots moving on a large table, such that the swarm of robots form a distributed table light and (b) Distributed odour source localization by Khepera robot equipped with volatile organic compound sensor and an anemometer (wind sensor). From <http://http://disal.epfl.ch>, last seen 01/06/2010.

- **Environmental state:** Free and blocked paths, level of interference found, any urgent event or dangerous changes found in the environment.
- **Intentions:** Detail plan for doing a task, sequences of selected actions etc.

Since a multi-robot system can be comprised of robots of various computation and communication capabilities, these information contents can vary greatly based on their individual communication modules and channel capacities.

4.3 Communication modalities

Robotic researchers typically use robot’s on-board wireless radio, infra-red (IR), vision and sound hardware modules for robot-robot and robot-host communication. The reduction in price of wireless radio hardware chips e.g. wifi (ad-hoc WLAN 802.11 network) or Bluetooth¹ makes it possible to use wireless radio communication widely. In-expensive IR communication module is also typically built into almost all mobile robots due to its low-cost and suitability for ambient light and obstacle detection. IR can also be used for low bandwidth communication in short-range, e.g. keen-recognition. Most robots can also produce basic sound waves and detect it with their built-in speakers and suitable configuration of on-board microphones. Although speech-recognition is not commonly found in mobile robots yet, detection of pre-recorded sound waves can be feasible.

Most of the mobile robots come with a series of LEDs, and tiny camera that can emit light signals and detect it with camera. Many robots can also detect blobs of colours and can recognize peers of other objects through the use of a color-coded markers. Some other researchers also tried to establish communication among robots solely relying on vision (Kuniyoshi et al., 1994). Although a lot of researches have been carried out to design robot skin and tactile communication system, we do not know any instance of tactile communication used in multi-robot team. In terms of chemical communication, Lochmatter et al. (2007) showed limited success in odour-source localization, a form of detecting chemical signals.

¹ www.bluetooth.com

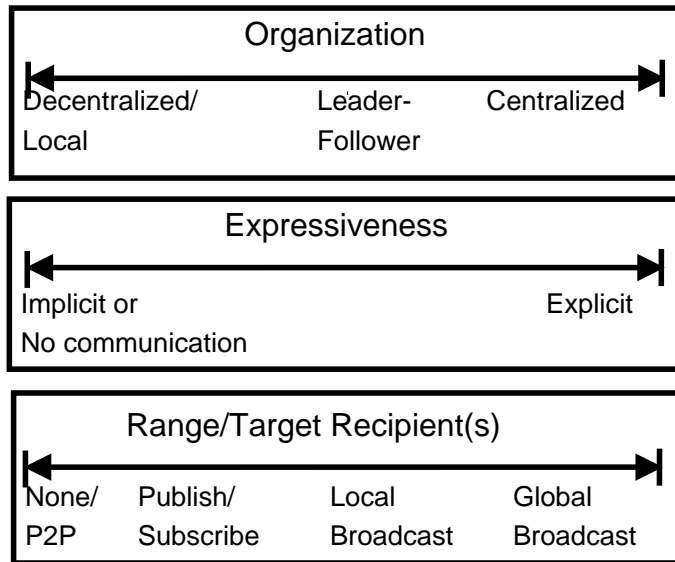


Figure 14. Three aspects of communication in multi-robot system

4.4 Communication strategies

Whatever be the communication modalities of a multi-robot system, suitable strategies are required to disseminate information in a timely manner to a target audience that maximizes the effective task-completion and minimizes delays and conflicts. A review of various communication strategies in social system has been presented in Sec. ???. Here, in order to discuss the complexities of communication strategies we have selected three independent scales: organization, expressiveness and range of communication. With these independent aspects, we can measure the level of complexities in communication and classify a multi-robot system according to its communication characteristics. Fig. 14 outlines these scales and we have described them below.

Centralized and decentralized communications

Similar to the organization of task-allocation discussed in Sec. ??, communication in a multi-robot system can be organized using an external/internal central entity (e.g. a server PC, or a leader robot) or, a few leader robots, or by using decentralized or local schemes where every robot has the option to communicate with every other robot of the team. From a recent study of multi-robot flocking Çelikkanat et al. (2008) have shown that a mobile robot flock can be steered toward a desired direction through externally guiding some of its members, i.e. the flock relies on multiple leaders or information repositories. Note that here task-allocation is fully decentralized i.e. each robot selects its task, but the communication structure is hybrid; robots communicate with each other and with a centralized entity.

Explicit and implicit communications

Communication in a multi-robot system can also be characterized its expressiveness or the degree of explicitness. In one extreme it can be fully implicit, e.g. stigmergic, or on the other

end, it can be fully explicit where communication is done by a rich vocabulary of symbols and meanings. Researchers generally tend to stay in either end based on the robotic architecture and task-allocation mechanism used. However, both of these approaches can be tied together under any specific application. They are highlighted below.

1. **Explicit or direct communication:** This is also known as intentional communication. This is done purposefully by usually using suitable modality e.g. wireless radio, sound, LEDs. Because explicit communication is costly in terms of both hardware and software, robotic researchers always put extra attention to design such a system by analysing strict requirements such as communication necessity, range, content, reliability of communication channel (loss of message) etc.
2. **Implicit or indirect communication:** This is also known as indirect stigmergic communication. This is a powerful way of communication where individuals leave information in the environment. This method was adopted from the social insect behaviour, such as stigmergy of ants (leaving of small amount of pheromone or chemicals behind while moving in a trail).

Local and Broadcast communications

The target recipient selection or determining the communication range or sometimes called radius of communication is an interesting issue in multi-robot system research. Researchers generally try to maximize the information gain by using larger range. However, transmission power and communication interference among robots play a major role to limit this range. The following major instances of this strategy can be used.

- **Global broadcast communication:** where all robots in the team can receive the message.
- **Local broadcast communication:** where a few robots in local neighbourhood can receive the message.
- **Publish-subscribe communication:** where only the previously subscribed robots can receive the message.
- **P2P communication:** where only the closest peer robot can receive the message.

Determination of local neighbourhood in multi-robot communication

Most researchers in the area of swarm-robotic system, who use algorithms based on local neighbourhood of communication, face this problem of defining the range of local neighbourhood. Agah & Bekey (1995) presented that larger communication range is not always optimum for some types of tasks e.g. exploration where a large number of recipient robots decreased the performance of exploration task. Yoshida & Arai (2000) provided a design of optimal communication range of homogeneous robots based on their spatial and temporal analyses of information diffusion within the context of cooperative tasks in a manufacturing shop-floor. Spatial design tried to minimize the time for information transmission and temporal design tried to minimize the information announcing time to avoid excessive information diffusion. Eq. 9 describes their optimal range $\chi_{optimal}$ as a function of information acquisition capacity of robots (c) and the probability of information output of a robot (p). Here c is an integer representing the upper-limit of the number of robots that can be the target recipients at any time without the loss of information and $\chi_{optimal}$ gives the average number of robots

within the output range.

$$\chi_{optimal} = \frac{\sqrt[p]{c!}}{p} \quad (9)$$

4.5 Role of communication in MRTA

Although researchers in the field of multi-robot system have been adopting various communication strategies for achieving MRTA solutions in different task domains, very few studies correlate the role of communication with the effectiveness of MRTA. This is due to the fact that researchers usually adopt a certain task-allocation method and they limit their use of communication strategy to either explicit global/local broadcast (in most predefined task-allocation researches) or implicit/no communication (in most self-organized task-allocation researches). In the former one, communication becomes the part and parcel of the robot-robot interactions that enable them to exchange variety of information as discussed before. But in the latter one, the environment serves as a shared memory for all robots to access information or sense the current state of the environment, mostly locally. Here we have attempted to scrutinize how MRTA solutions have been affected by the variations in communication strategies.

As mentioned in Sec. ??, Kalra & Martinoli (2007) empirically studied the comparative performance of MRTA under both predefined and self-organized approaches with event-driven simulations. They found that the accuracy of information is crucial for predefined market-based approach where every robot communicated with every other robot (i.e. global broadcast). In case of unreliable link or absence of communication, threshold-based approach performed same as market-based approach, but with less computational overhead. This indicates the dependence of predefined approach on reliable communication links. However their global broadcast strategy is not feasible for large teams of real-robots. In case of varying robot's communication range, they found that market-based approach performed well for a short communication-range where robots were able to communicate with less than a third of the total number of team-mates. Since the events are handled based-on their spatial locations only, it is not clear how this strategy will perform in other task-domains.

In order to pursue MRTA, robots can receive information from a centralised source Krieger & Billeter (2000) or from their local peers (Agassounon & Martinoli, 2002). This centralized communication system is easy to implement. It simplifies the overall design of a robot controller. However as we mentioned before, this system has disadvantage of a single point of failure and it is not scalable. The increased number of robots and tasks cause inevitable increase in communication load and transmission delay. Consequently, the overall system performance degrades. On the other hand, uncontrolled reception of information from decentralized or local sources is also not free from drawbacks. If a robot exchanges signals with all other robots, it might get the global view of the system quickly and can select an optimal or near optimal task. This can produce a great improvement in overall performance of some types of tasks e.g., in area coverage Rutishauser et al. (2009). But this is also not practical and scalable for a typically large multi-robot system due to the limited communication and computational capabilities of robots and limited available communication bandwidth of this type of system.

A potential alternate solution to this problem can be obtained by decreasing the number of message recipients on the basis of a local communication range. This means that robots are allowed to communicate only with those peers who are physically located within a pre-set distance. When this strategy is used for sharing task information among peers, MRTA can be more robust to the dynamic changes in the environment and energy- efficient (Agassounon & Martinoli, 2002). Similair to this, Pugh & Martinoli (2009) reported a distributed multi-robot

learning scenario with two cases: 1) robots were allowed to communicate with any two other robots (*Model A*) and 2) robots were allowed to communicate with all robots in a fixed radius (*Model B*). In simulation and real robotic experiments with 10 robots and communication ranges of 0.3 m, 1.0 m and 3.3 m, they showed that Model B performed better in intermediate communication range. However, these learning process of individual robot controller were conducted in static environment. So it is not clear why intermediate communication range performs better than other ranges.

Many robotic researchers tried to use some forms of adaptation rules in local communication to avoid saturation of the communication channel, e.g. based on robot densities in a given area. As mentioned before, Yoshida & Arai (2000) tried to formalize the suitable communication range based on spatial and temporal properties of information diffusion of a given communication channel. The major focus of this type of research is to measure the cost of communication based on some metrics, e.g. transmission time and collisions with other robots, and then regulate communication strategies or ranges dynamically ranging from global broadcast to local P2P or not doing communication at all when a huge cost is involved. These ideas are attractive to maximize information gain in dynamic environment, but there is no point of doing communication if there is little or no task-requirement. Thus we find this approach, i.e. maximizing information gain, is not always useful or necessary for effective MRTA.

Oca et al. (2005) also acknowledged the above fact within the context of their ant-based clustering experiments. They used two simple communication strategies: 1) simple memory sharing by robots (shared memory access) and 2) shared use of environment maps (global sensing). In both of these cases, it was found that communication is only useful when some initial random clustering phase was passed. The accuracy of shared information in highly dynamic environment was poor and did not carry any significant advantage. In case of local memory sharing by robots, they showed that sharing information within a limited number of robots produced more efficient clusters, rather than not sharing information at all in stigmergic communication mode. However, sharing memory in a large group is not a feasible communication strategy because of the huge latencies and interferences involved in the communication channel.

5. Validation of AFM under bio-inspired communication strategies

5.1 Global sensing – no communication

5.2 Local sensing – local communication

6. Conclusion

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