Communication Strategies for Self-regulated Multi-robot Task Allocation

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Chapter 1

Introduction

1.1 Multi-robot task allocation (MRTA)

Robotic researchers generally agree that multiple robots can perform complex and distributed tasks more conveniently. Multi-robot systems (MRS) can provide improved performance, fault-tolerance and robustness through parallelism and redundancy (Arkin 1998, Parker & Tang 2006, Mataric 2007). However, in order to get potential benefits of MRS in any application domain, we need to solve a common research challenge i.e., *multi-robot task allocation* (MRTA) (Gerkey & Mataric 2004). MRTA can also be called as *division of labour* (DoL) analogous to DoL in biological social insect and human societies (hereafter the term MRTA is used to denote an instance of social DoL). It 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. This is a NP-hard optimal assignment problem where optimum solutions can not be found quickly for large complex problems (Gerkey & Mataric 2003, Parker 2008). The complexities of MRTA arise from the fact that there is no central planner or coordinator for task assignments and the robots are limited to sense, to communicate and to interact locally. None of them has the complete knowledge of the past, present or future actions of other robots. Moreover, they don't have the complete view of the world state. The computational and communication bandwidth requirements also restrict the solution quality of the problem (Lerman et al. 2006).

Researchers from multi-robot or multi-agent systems, operations research and other disciplines have approached the MRTA or task-allocation in multi-agents issue in

many different ways. Traditionally task allocation in a multi-agent systems has been divided into two major categories: 1) Predefined (off-line) and 2) Emergent (real-time) task-allocation (Shen et al. 2001). However predefined task- allocation approach fails to scale well as the number of tasks and robots becomes large, e,g,, more than 10 (Lerman et al. 2006). On the other hand emergent task-allocation approach relies on the emergent group behaviours e.g., (Kube & Zhang 1993), such as emergent cooperation (Lerman et al. 2006), adaptation rules (Liu et al. 2007) etc. They are more robust and scalable to large team size. However most of the robotic researchers found that emergent task-allocation approach is difficult to design, to analyse formally and to implement in real robots. The solutions from these systems are also sub-optimal. It is also difficult to predict exact behaviours of robots and overall system performance.
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 MRTA problem in a new way (Arcaute et al. 2008). Our approach is inspired from the studies of emergence of task-allocation in both biological insect societies and human social systems. Biological studies show that a large number of animal as well as human social systems grow, evolve and generally continue functioning well by the virtue of their individual self-regulatory task-allocation systems. The amazing abilities of biological organisms to change, to respond to unpredictable environments, and to adapt over time lead them to sustain life through biological functions such as self-recognition, self-recovery, self-growth etc. It is interesting to note that in animal societies task-allocation has been accomplished years after years without a central authority or an explicit planning and coordinating element. Direct peer-to-peer (P2P) and indirect communication such as stigmergy is used to exchange information among individuals (Camazine et al. 2001). The decentralized self-growth of Internet and its bottom-up interactions of millions of users around the globe present us similar evidences of task-allocation in human social systems (Andriani & Passiante 2004). These interactions of individuals happen in the absence of or in parallel with strict hierarchy. Moreover from the study of sociology e.g., (Sayer & Walker 1992), cybernetics e.g., (Beer 1981), strategic management e.g., (Kogut 2000) and related other disciplines we have found that decentralized self-regulated systems exist in

nature and in man-made systems which can grow and achieve self-regulated division of labour over time.

From the above mentioned multi-disciplinary studies of various complex systems, we believe that a set of generic rules can govern the self-regulated task-allocation in MRS. Primarily these rules should deal with the issue of deriving local control rules for facilitating the task-allocation of an entire robot team.

The outcome of our research can be applied to solve generic task-allocation problem in numerous multi-agent systems. As an example, our technique can be useful in automated manufacturing (AM) which faces all the existing challenges of traditional centralized and sequential manufacturing processes such as, insufficiently flexible to respond and adapt changes in production styles of high-mix low-volume production environments (Shen et al. 2006). We believe that our approach can help AM industries to overcome many of these challenging issues, such as flexibility to change the manufacturing plant layouts on-the-fly, adaptability for high variation in product styles, quantities, and active manufacturing resources e.g., robots, AGVs etc.

1.2 Communications for self-regulated task-allocation

In MRS research, robotic researchers have been using various forms of communications e.g., (Bonabeau et al. 1999, Labella 2007). Two widely used forms of communications are: 1) direct or explicit communication and 2) indirect or implicit communication. *Direct communication* is an intentional communicative act of message passing that aims at one or more particular receiver(s) (Mataric 1998). It typically exchanges information through physical signals. In contrast, indirect communication, sometimes termed as *stigmergic* in biological literature, happens as a form of modifying the environment (e.g., pheromone dropping by ants) (Bonabeau et al. 1999). In ordinary sense, this is an observed behaviour and many robotic researchers call it as *no communication* (Labella 2007). In order to avoid ambiguity, by the term *self-regulated MRTA* (or *MRTA* for short) we refer to those MRS where robots can exhibit most common self-regulatory properties (Bonabeau et al. 1999) in their task-allocation process. Also in this thesis, by the term *communication*, we always refer to direct communication and we confine our discussion on MRTA within the context of direct communication only.

In the process of pursuing self-regulated MRTA, robots can receive information from a centralised source (Krieger & Billeter 2000) or from their local peers (Agassounon et al. 2004). In (Sarker & Dahl n.d.), we reported a steady-state convergence of MRTA in a practical MRS using a centralized information source. This centralized communication system is easy to implement. It simplifies the overall design of a robot controller. However 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 (hereafter called as *peers*), 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 MRS 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 recipient peers on the basis of a local communication radius (r_{comm}). 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 and efficient (Agassounon et al. 2004). However it is not well-defined how the selection of communication range can be made despite the significant differences in various implementation of MRS. In case of biological social insects, the concept of *active space* explains how each individual set their dynamic communication radius (Holldobler & Wilson 1990, McGregor & Peake 2000) (see Section **??**). In this thesis, we present a locality based dynamic P2P communication model that design a desired communication range by considering both biological inspirations and geometric relationships of the environment particularly, the shapes and communication capabilities of robots. Along with a practical insight for selecting r_{comm} value, various other design issues have been tackled. The recursion-free design of local communication channels is also achieved by a dynamic publish/subscribe model of communication. We also compare this system with our baseline centralized communication based MRS in terms of convergence of MRTA, communication load, robot motions and their task specializations.

1.3 Contributions

The main contributions of this thesis are as follows:

- Introduction of attractive field model (AFM), an inter-disciplinary generic model of division of labour, as a basic mechanism of self-regulated MRTA.

- Validation of the model through experiments with reasonably large number of real robots.

- Development of a centralized and a local P2P communication model and their respective implementation algorithms that satisfy the requirement of system-wide continuous flow of information for self-regulated task-allocation.

- Comparisons of performances of both communication models in achieving similar self-regulated MRTA.

- Development of a point-to-point signal based multi-robot control architecture using D-Bus inter-process communication technology.

1.4 Thesis outline and relevant publications

This report has been organized as follows. Chapter 2 reviews the reviews the related literature on general terms, key issues of MRS and MRTA. This also includes the review of communication for self-regulated task-allocation in biological societies. This chapter concludes by discussing the related work on communication for self-regulated MRTA. Chapter 3 describes the attractive filed model in details. Chapter 4 presents the our centralized and local communication models and analyse it from the geometric and biological view-point. Chapter 5 includes experiment tools used in this research. Chapter 6 describes the design of our experiments. Chapter 7 describes the results of our experiments. Chapter 8 concludes this thesis with a summary and future research directions.

Chapter 2

Background and Related Work

2.1 Definition of key terms

2.1.1 Self-regulation

Animals and flying beings that live on or above earth form social communities like human society (Ali 1995). In recent years, the biological study of social insects and other animals reveals us that individuals of these self-organized societies can solve various complex and large everyday-problems with a few simple behavioural rules relying on their minimum sensing and communication abilities (Garnier et al. 2007, Camazine et al. 2001). Some common tasks of these biological societies include: dynamic foraging, building amazing nest structures, division of labour among workers and so forth. These tasks are done by colonies, ranging from a few animals to thousands or millions of individuals, that exhibit surprising efficiency in their tasks with both robustness and flexibility. Today these findings have inspired scientists and engineers to use this knowledge of biological self-organization in developing solutions for various problems of our man-made artificial systems, such as traffic routing in telecommunication and vehicle networks, design control algorithms for groups of autonomous robots and so forth.

Self-organization in biological and other systems are often characterized in terms of four major ingredients: 1) Positive feedback, 2) Negative feedback, 3) Presence of multiple interactions among individuals and their environment and 4) Amplification of fluctuations (random walks, errors, random task-switching etc.) (Bonabeau et al. 1999, Camazine et al. 2001). As illustrated in Fig. 2.1 an external observer can recognize a self-organized system by observing the individual

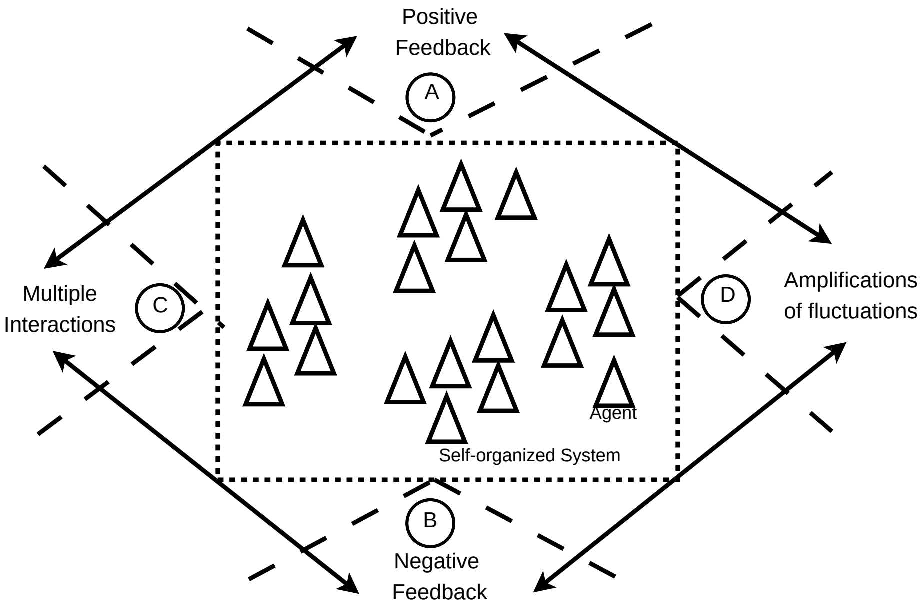

Figure 2.1: Self-organization viewed from four (A-D) inseparable perspectives

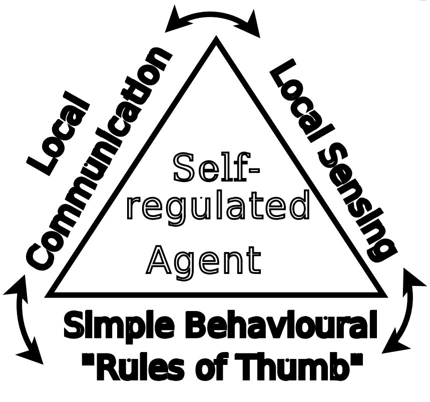

Figure 2.2: Three major parts of a self-regulated agent

interactions of that system from these four perspectives. The first perspective is a positive feedback or amplification that results from the execution of simple behavioural “rules of thumb”. For example, recruitment to a food source through trail laying and trail following in some ants is a positive feedback that creates the conditions for the emergence of trail network at the global (or an outside observer) level. The second perspective is negative feedback that counterbalances positive feedback usually to stabilize a collective patterns, e.g., crowding at the food sources (saturation), competition between paths to food sources etc. The third perspective is the presence of multiple direct peer-to-peer or indirect stigmergic (e.g., pheromone dropping in ants) interactions. The former is the main concern of this thesis and is discussed latter in detail. Finally, the fourth perspective is the amplification of fluctuations that comes from the stochastic events. For example errors in trail following of some ants may lead some foragers to get lost and later to find new, unexploited food sources and then recruit others. In a self-organized system an individual agent may have limited cognitive, sensing and communication capabilities, but they are collectively capable of solving complex and large problems. Since the discovery of these collective behavioural patterns of self-organized societies scientists observed modulation or adaptation of behaviours in the individual level. For example, in order to prevent a life-threatening humidity-drop in the colony, cockroaches maintain a locally sustainable humidity level by increasing their tendency to aggregate, i.e., by regulating their individual aggregating behaviours (Garnier et al. 2007). As shown in Fig. 2.2 this self-regulation (SR) of an individual agent is depicted through a triangle where it’s base-arm of simple behavioural rules of thumb (e.g., intense aggregation in low humidity in the previous example) is supported by two side-arms: local communication and local sensing. This local sensing is sometimes also referred to as sensing or information gathering from the work in progress (e.g., stigmergy) and the local communication mentioned here is directly linked with peer-to-peer (P2P) communication with neighbours (Camazine et al. 2001).

SR has been studied in many other branches of knowledge. In most places of literature, SR refers to the exercise of control over oneself to bring the self into line with preferred standards (Baumeister & Vohs 2007). One of the most notable self-regulatory process is the human body’s homoeostatic process where the human body’s inner process seeks to return to its regular temperature when it gets overheated or chilled. Baumeister et al. has referred self-regulation to goal-directed behaviour or feedback loops, whereas self-control may be associated with conscious impulse control. In psychology, SR denotes the strenuous actions to resist temptation or to overcome anxiety. SR is also divided into two categories: 1) conscious and 2) unconscious SR. Conscious SR puts emphasis on conscious, deliberate efforts in self-regulation. On the other hand, unconscious self-regulation refers to the automatic self-regulatory process that is although not nearly as labour intensive, but operate in harmony with unpredictable, unfolding events in the environment, using and transforming the available informational input in ways that help to attain an activated goal.

The concepts of SR is also commonly used in cybernetic theory where SR in inanimate mechanisms shows that they can regulate themselves by making adjustments according to programmed goals or set standards. A common example of this kind can be found in a thermostat that controls a heating and cooling system to maintain a desired temperature in a room. In physics, chemistry, biology and some other branches of natural sciences, the concept of SR is centred around the study of self-organizing individuals. SR has also been studied in the context of human social systems where it originates from the division of social labor that creates SO process that has self-regulating effects (Kppers et al. 1990). Two types of SR have been reported in many places of literature of sociology: 1) SR from SO and 2) SR from activities of components in a heterarchical organization. It is interesting to note that self-regulation in biological species provides the similar evidences of bottom-up approach of self-regulation of heterarchical organization through interaction of individuals or the absence of strict hierarchy Beer1981.

From the above discussion, we see that the term *self-regulation* carries a wide range of meaning in different branches of knowledge. In psychology and cognitive neuroscience point of view, self-regulation is discussed in an individual's perspective whereas, in biological and social contexts the SR is discussed in a context of a group of individuals or the society as a whole. In this thesis, the latter context is more appropriate where SR covers both aspects of monitoring ones own state and environmental changes in relation to the communal goal and thus making adjustments of self behaviours with respect to the changes found.

2.1.2 Communication

Defining *communication* can be challenging. Due to the use of this term in several disciplines with somewhat different meanings. This has been potrayed in the writing of Sarah Trenholm ((West 2003)) who describes communication as piece of luggage overstuffed with all manner of odd ideas and meanings. This dissertation closely follows the definition of (West 2003) where communication is defined as:

> “A social process where individuals employ symbols to establish and interpret meaning in their environment.”

The notion of being a “social process” involves (two or more) individuals and interactions that is dynamic and ongoing. Moreover symbols are simply some sort of arbitrary labels given to a phenomena and they can represent concrete objects or an idea or thought. Encyclopaedia Britannica also defines communication as “the exchange of meanings between individuals through a common system of symbol”. But since it ;lacks the notion of sociality I consider it incomplete for our purpose. There are many other debates related to communication, such as the intentionality debate (West 2003), symbol grounding and so on. However, in order to draw some tractable boundaries , I consider communication process within the context of symbol or message exchange between two or more parties with a clear intent to influence each others’ behaviours.

The elements of communication can give us us the whole picture involved in communication process and this can be explained through the study of the models of communication. There exists a plenty of models of communication. For the purpose of this study, here I discuss three prominent models: 1) linear model, 2) interaction model and 3) transaction model. Fig. **??** combines first two models in a single diagram. In linear model, as introduced by Claude Shanon and Warren Weaver (1949), communication is a one way process where a message is sent from a source to a receiver through a channel. On top of linear view, in interactional model proposed by Wilber Schramm (1954), communication is a two-way process with an additional feedback element that links both source and receiver. This feedback is a response given to the source by the receiver to confirm how the message is being understood. Here, during message passing, both source and receiver utilize their individual field of experiences that describe the overlap of their common experiences, cultures etc. Unlike separate filed of experiences and discrete sending and receiving of message in interactional model, in transactional model, introduced by Barnlund(1970), the sending and receiving of message is done simultaneously and their field of experiences also overlaps to some degree. In all of the above three models a common message distorting element, i.e., noise is present. This noise can be occurred from the linguistic influences (message semantics), physical or bodily influences, cognitive influences or even from biological or physiological influences (e.g., anger or shouting voice while talking) and so on.

The above models of communication describe the incremental complexities of message exchanging in a communication process. Surely the transactional model is comparatively the most sophisticated model that prescribes adjusting the sender's message content while receiving an implicit or explicit feedback in real-time. For example, while speaking with her son for advising to read a story book, a mother may alter her verbal message as he simultaneously "reads" the non-verbal message of her child. However, in case of MRS, such sophistication may not be required or realizable by the current state of art in communication technology. In this study we follows the simple linear model that gives us the ease of implementation. The feedback is not accounted as we assumed that our artificial robotic system has a same shared vocabulary so that a message is understood as it is sent. Sender never waits for an additional feedback to end sending a message.

Following the linear model of communication, the amount of communicated information associated with a certain random variable X can be calculated by the concept of *Shanon entropy*. Adopting the notation of Feldman (Feldman 1997), and indicating a discrete random variable with the capital letter X, which can take values $x \in \chi$, the information entropy is defined as:

$$H[X] = -\sum_{x \in \chi} p(x) \cdot \log_2 p(x) \tag{2.1}$$

where p(x) is the probability that X will take the value of x. H[X] is also called the *marginal* entropy of X, since it depends on only the marginal probability of one random variable. The marginal entropy of the random variable X is zero if X always assumes the same value with p(X =x)= 1, and maximum if X assumes all possible states with equal probability.

For example, in order to measure information flow in an elementary communication system, let *bit* be the unit amount of information needed to make a choice between two equiprobable alternates. If *n* alternates are present, a choice provides the following quantity of information: $H = log_2\ n$. Thus sending of n equiprobable messages reduces $log_2\ n$ amount of uncertainty and thus the amount of information is $log_2\ n$ bit. Similarly, according to Eq. 2.1, the value of H[X] depends on the discretization of x. For instance, if the value of random variable x is discretized into 4, then p(x) becomes $\frac{1}{4}$ leading to H[X] = - $4 \cdot \frac{1}{4} \cdot log_2\ \ \frac{1}{4}$ = 2.

In biological and MRS literature two basic forms of communications often are reported: 1) direct or explicit communication and 2) indirect or implicit communication. As defined in (Mataric 1998), *direct communication* is an intentional communicative act of message passing that aims at one or more particular receiver(s). It typically exchanges information through physical signals. In contrast, *indirect communication*, sometimes termed as *stigmergic* in biological literature, happens as a form of modifying the environment (e.g., pheromone dropping by ants) (Bonabeau et al. 1999). In ordinary sense, this is an observed behaviour and many robotic researchers call it as *no communication* (Labella 2007). In order to avoid ambiguity, in this dissertation, by the term *communication*, I always refer to direct communication. Sec. 2.2 and 2.5 reviews communication in biological social system and MRS respectively.

2.1.3 Division of labour or task-allocation

Encyclopaedia Britannica serves the definition of division of labour as the separation of a work process into a number of tasks, with each task performed by a separate person or group of persons. Originated from economics and sociology the term division of labour is widely used in many branches of knowledge. As mentioned by Scottish philosopher Adam Smith, the founder of modern economics :

> The great increase of the quantity of work which, in consequence of the division of labour, the same number of people are capable of performing, is owing to three different circumstances; first, to increase the dexterity in every particular workman; secondly, to the saving of the time which is commonly lost in passing from one species of work to another; and lastly, to the invention of a great number of machines

> which facilitate and abridge labour, and enable one man to do the work of many.
> (Adam Smith (1776) in (Sendova-Franks & Franks 1999))

In sociology, division of labour usually denotes the work specialization (Sayer & Walker 1992). Basically it answers three questions:

1. *What task?* i.e., the description of the tasks to be done, service to be rendered or products to be manufactured.

2. *Why dividing it to individuals?* i.e., the underlying social standards for this division, such as task appropriateness based on class, gender, age, skill etc.

3. *How to divide it?* i.e.,the method or process of separating the whole task into small pieces of tasks that can be performed easily.

In the study of biological insects, 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 division of labour among nest-mates, whereby different activities are performed simultaneously by groups of specialized individuals, is believed to be more efficient than if tasks were performed sequentially by unspecialised individuals. Division of labour has a great *plasticity* where the removal of one class of workers is quickly compensated for by other workers. Thus distribution 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 MRS, the term “division of labour” is often found synonymous to “task-allocation” . However, some researchers (e.g. (Labella 2007)) argued to distinguish these terms due to the origin and particular contextual use of these terms. Particularly, division of labour adopts the biological notion of collective task performance with little or no communication. On the other hand, task allocation follows the meaning of assigning task(s) to particular robot(s) based on individual robot capabilities, typically through explicit communication, such as *intentional cooperation* (Parker 1998). The former is considered under *swarm robotics (SR)* paradigm and latter is done under *traditional MRS*. Sec. 2.3 covers both of these approaches in more detail.

In this dissertation, I closely follow the SR approach for the defining division of labour, but I do not put any restriction on the use of communication. In fact, I view division of labour as a group-level phenomenon which occur due to the individual agent's self-regulatory task selection behaviour. But, unlike SR approach that view communication as expensive and hence try to find solutions avoiding it, I do not advocate for restricting the use of communication. Rather, for the following reasons, along with our generic mechanism of division of labour, i.e. AFM (Chapter 4), I propose some self-regulatory communication strategies to vary communication load dynamically (Chapter 6).

Firstly, from our understaning of different kinds of communication strategies of biological social systems (Sec. 2.2), this is obvious that the role of communication can not be ignored for achieving division of labour in MRS. Instead of being too much addicted to communication-less algorithms, perhaps due to the limitation of current communication technology (such as mimicking biological stigmergy), we need to exploit the existing state of the art in communication technology for developing functional and robust division of labour mechanisms for future MRS. By selecting a suitable communication strategy and enabling robots to self-regulate their certain behaviours, we can significantly reduce the communication load of a MRS.

Secondly, Whatever be the objectives of a target MRS under any of the above approaches, e.g., maximizing robustness, scalability and/or task performance, the issue of task-allocation of an individual robot remains same, i.e., what task should it select at a particular time point considering dynamically changing task requirements, choices of peer robots and environmental conditions. In this issue, unlike traditional MRS approach, I emphasize on maintaining the overall group level performance and robustness, not just focusing on the instantaneous maximum benefit (or minimum cost) of a robot by performing a particular task.

Finally, by combining the above two points, I define division of labour in MRS as a self-regulated task allocation process of a group of robots, where robots can dynamically select suitable tasks, or can switch from one task to another based on continuously sensed and communicated information of tasks, states etc. through their respective sensory and communication channels. Thus, by adopting this self-regulated task selection and communication strategies, some of the robots can have chances to specialize on some particular tasks, and as a whole, the system can maintain a level of plasticity without producing unnecessary communication burden on the system.

2.2 Communication in biological social systems

Communication plays a central role in self-regulated division of labour of biological societies.In this section communication among biological social insects are briefly reviewed within the context of self-regulated division of labour.

Communication in biological societies serves many closely related social purposes. Most peer-to-peer (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. 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 such as in courtship display. In ants and some other social insects chemical communication is dominant. 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 glandular secretion, used for communication within species. One individual releases it as a signal and others responds it after tasting or smelling it. Using pheromones individuals can code quite complicated messages in smells. For example a typical an ant colony operates with somewhere between 10 and 20 kinds of signals (Holldobler & Wilson 1990). 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 nestmate for foraging or other tasks it runs upto a nestmate 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 there nerves and muscles work as batteries. They use continuous or intermittent pulses with different frequencies learn about environment and to convey their identity and aggression messages. The concept of active space 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 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: The amount of pheromone emitted (Q) The threshold concentration at which the receiving animal responds (K) 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. 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 by 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 or 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). As the 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 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 *Aphaeonogerter* 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.

2.3 Overview and key issues of multi-robot systems (MRS)

Historically the concept of multi-robot system comes almost after the introduction of behaviour-based robotics paradigm (Brooks 1986, Arkin 1990). In 1967, using the traditional sense-plan-act or hierarchical approach (Murphy 2000), the first Artificially Intelligent (AI) robot, Shakey, was created at the Stanford Research Institute. In late 80s, Rodney A. Brooks revolutionized this entire field of mobile robotics who outlined a layered, behaviour based approach that acted significantly differently than the hierarchical approach (Brooks 1986). At the same time, Valentino Braitenberg described a set of experiments where increasingly complex vehicles are built from simple mechanical and electrical components (Braitenberg 1984). Around the same time and with similar principle, Reynolds developed a distributed behavioural model for a bird in a flock that assumed that a flock is simply the result of the interactions among the individual birds (Reynolds 1987). Early research on multi-robot systems also include the concept of cellular robotic system (Fukuda & Nakagawa 1987), (Beni 1988) multi-robot motion planning (Arai et al. 1989, Premvuti & Yuta 1990, Wang 1989) and architectures for multi-robot cooperation (Asama et al. 1989).

From the beginning of the behaviour based paradigm, the biological inspirations influenced many cooperative robotics researchers to examine the social characteristics of insects and animals and to apply them to the design multi-robot systems (Arkin 1998). The underlying basic idea is to use the simple local control rules of various social species, such as ants, bees, birds etc., to the development of similar behaviours in multi-robot systems. In multi-robot literature, there are many examples that demonstrate the ability of multi-robot teams to aggregate, flock, forage, follow trails etc. (Bonabeau et al. 1999, Mataric 1994). The dynamics of ecosystem, such as cooperation, has also been applied in multi-robot systems that has presented the emergent cooperation among team members (McFarland 1994), (Martinoli et al. 1996). On the other hand, the study of competitive behaviours among animal and human societies has also been applied in multi-robot systems, such as that found in multi-robot soccer (Asada et al. 1999).

2.3.1 MRS research paradigms

As discussed above, there are several research groups who follow different approaches to handle multi-robot research problems. Parker (Parker 2008) has summarized most of the recent research approaches into three paradigms:

1. Bioinspired, emergent swarms paradigm,
2. Organizational and social paradigm and
3. Knowledge-based, ontological and semantic paradigm

Bioinspired, emergent swarms paradigm

In bio-inspired, emergent swarms paradigm local sensing and local interaction forms the basis of collective behaviors of swarms of robots. Many researchers addressed the issues of local interaction, local communication (i.e., stigmergy) and other issues of this paradigm (Mataric 1995), (Kube & Zhang 1993). Today, this paradigm has been emerged as a sub-field of robotics called swarm robotics (Sahin & Spears 2005). This is a powerful paradigm for those applications that require performing shared common tasks over distributed workspace, redundancy or fault-tolerance without any complex interaction of entities. Some examples include flocking, herding, searching, chaining, formations, harvesting, deployment, coverage etc.

Swarm robotics is a relatively new branch of robotics where a large number of collective robots are studied from the inspiration of the observation of social insects ants, termites wasps and bees (Sahin & Spears 2005). The term swarm intelligence was first coined by Gerado Beni (Beni 2005) in late 1980s and during recent years the term swarm robotics emerged as an application of swarm intelligence to multi-robot systems with emphasis on physical embodiment of entities and realistic interactions among the entities and between the entities and their environment. In order to distinguish swarm robotics from other branches of robotics such as collective robotics, distributed robotics, robot colonies and so forth, Sahin proposed a formal definition and a set of criteria for swarm robotics research (Sahin & Spears 2005). According to him, swarm robotics is the study of how large number of relatively simple physically embodied agents can be designed such that a desired collective behaviour emerges from the local interactions among agents and between the agents and the environment. And the notable criteria of swarm robotics research are listed as follows.

Autonomous robots that exclude the sensor networks and may include metamorphic robotic system without having no centralized planning and control element.

Large number of robots, usually $\geq$ 10 robots, or at least having provision for scalability if the group size is below this number.

Mostly homogeneous groups of robots that typically exclude the multi-robot soccer teams having heterogeneous robots.

Relatively incapable of inefficient robots that is the task complexity enforces either cooperation among robots or increased performance or robustness without putting no restriction on individual robot's hardware/software complexity.

Robots with local sensing and communication capabilities that does not use global coordination channel to coordinate among themselves, rather enforces distributed coordination.

Modelling the swarms is a key issue in swarm robotics. This is aimed for investigating suitable models and algorithms for control and task-allocation of swarms of robots. A review of models and approaches for coordination and control of dynamic multi-agent systems by (Gazi & Fidan 2006) presented that a number of approaches can be used to model swarm robotic systems with the specific focus on major issues like stability, performance, robustness and scalability. Based on the relevance to our study, we have discussed them as follows.

Behaviour-based approaches: The ease of implementation of a behaviour-based robotic system has inspired researchers to follow behaviour-based approaches for modelling swarm robotic systems using variety of specific swarm behaviours. Early research of Reynold provided the example of a behaviour-based approach for swarm coordination such as, flocking of birds (Reynolds 1987). Recent studies on behaviour-based approaches include the work of (Balch & Arkin 1998) where they have evaluated the formation acquisition and stabilization of multi-robot systems. Several other researchers used other techniques, such as use of adaptation rules (Liu et al. 2007), collective behaviours (Cianci et al. 2007) etc., for implementing a behaviour-based swarm robotic system.

Probabilistic approaches: Probabilistic approaches and Markov models also present attractive alternatives for modelling of swarm behaviour. They typically use the population level swarming dynamics in a non spatial way in terms of frequency distributions of groups of various size (Gazi & Fidan 2006). A recent review of probabilistic approaches for swarm modelling is presented in (Lerman et al. 2005).

Asynchronous swarm model based approaches: Asynchronous multi-agent dynamic systems are difficult to tract for analysis and are not widely found in literature. One of the pioneer study by (Beni & Liang 1996) provided sufficient conditions for the asynchronous convergence of linear swarm to a synchrously achievable configuration. Some other recent studies can be found in (Gazi & Fidan 2006).

Control theoretic approaches: Control theoretic approaches include potential field, feedback linearisation, sliding mode, and various non-linear control approaches, e.g., Fuzzy, Neural nets, Knowledge-based/Rule-based, Lyapunov analysis etc. In recent years, combined or hybrid approaches, e.g., neuro-fuzzy, are also being adopted for modelling swarm behaviours and learning parameter settings of a system (Sahin et al. 2007).

Artificial Physics based approaches: Artificial physics based approaches use the fundamental laws of physics such as the Newton's laws of motion to model swarm robotic systems. In a pioneering work by (Spears & Gordon 1999), this approach has been illustrated and since then many development has been taken place under this framework to address the issue of formation stabilization, surveillance, coverage of a region etc.

Multi-agent based and other approaches: Since the field of swarm intelligence and swarm robotics is expanding contentiously many researchers are putting efforts to bring newer swarm models based on multi-agent based other techniques which are not reviewed here explicitly.

Organizational and social paradigm

Organizational and social paradigms are typically based on organization theory derived from human systems that reflects the knowledge from sociology, economics, psychology and other related fields. To solve complex problems this paradigm usually follows the cooperative and collaborative forms of distributed intelligence. In multi-robot systems the example of this paradigm is found in two major formats:

the use of roles and value system and market economics. In multi-robot applications under this paradigm, an easy division of labor is achieved by assigning roles depending on the skills and capabilities in individual team member. For example, in multi-robot soccer (Stone & Veloso 1999, Asada et al. 1999) positions played by different robots are usually considered as defined roles. On the contrary, in market economics approach (Gerkey & Mataric 2002, Dias et al. 2006) task allocation among multiple robots are done via market economics theory that enables the selection of robots for specific tasks according to their individual capabilities determined by a bidding process.

Knowledge-based, ontological and semantic paradigm

The third paradigm, commonly used for developing multi-agent systems, is knowledge-based, ontological and semantic paradigm. Here knowledge is defined as ontology and shared among robots/agents from disparate sources. It reduces the communication overhead by utilizing the shared vocabulary and semantics. Due to low bandwidth, limited power, limited computation and noise and uncertainty in sensing/actuation, the use of this approach is usually restricted in multi-robot systems.

Although this approximate classification includes most of the research directions it is very hard to specifically categorize all diverse researches on multi-robot systems. However, most of the researchers select a suitable paradigm to abstract the problem from an specific perspective with a fundamental challenge to determine how best to achieve global coherence from the interactions of entities at the local level.

Whatever the principle characteristics of a MRS, e.g., homogeneity, coupling, communication methods etc., each MRS must address some basic problems to some degree. For example, usually every MRS adopts a control architecture under a specific paradigm. Similarly every MRS address the issues of communication, localization, interaction in a way specific to the application and underlying design principles (or philosophies). In the following subsections, we have attempted to summarize the key MRS research issues that would influence the selection and implementation our research. In this initiative we have deliberately omitted the non-central or very specific issues, such as collaborative transport or reconfigurable MRS, that does not directly relate to our research.

2.3.2 Swarm Robotics

2.3.3 Architecture and control

In MRS, two high-level control strategies are very common: 1) centralized and 2) decentralized or distributed. Under a specific control strategy, traditionally three basic system architectures are widely adopted: deliberative, reactive and hybrid. Deliberative systems based on central planning are well suited for the centralized control approach. The single controller makes a plan from its Sense-Plan-Act (SPA) loop by gathering the sensory information and each robot performs its part. Reactive systems are widely used in distributed control where each robot executes its own controller maintaining a tight coupling between the system's sensors and actuators, usually through a set of well-designed behaviours. Here, various group behaviour emerges from the interactions of individuals that communicate and cooperate when needed. Hybrid systems are usually the mixture of the two above approaches; where each robot can run its own hybrid controller with the help of a plan with necessary information from all other robots. (Mataric 2007) described behaviour-based control architecture as a separate category of distributed control architecture where each robot behaves according to a behaviour-based controller and can learn, adapt and contribute to improve and optimize the group-level behaviour. Although most of the MRS control architectures share some common characteristics (such as distributed and behaviour-based control strategy) based on their difference of underlying design principles we have put them into three groups:

1. Behaviour-based classical architectures

2. Market-based architectures

3. Multi-agent based architectures

Due to the overwhelming amount of literature on MRS architectures it is not possible to include most of them. However, below some representative key architectures strictly designed for MRS are described.

Behaviour-based classical architectures

The ALLIANCE architecture (Parker 1998) is one of the earliest behaviour-based fully distributed architectures. This architecture has used the mathematically modelled behaviour sets and motivational system. The primary mechanism for task selection of a robot is to activate the motivational behaviour partly based on the estimates of other robots behaviour. This architecture was designed for heterogeneous teams of robots performing loosely coupled tasks with fault-tolerance and co-operative control strategy. Broadcast of local eligibility (BLE) (Werger & Mataric 2001) is another behaviour-based architecture that uses port-attributed behaviour technique through broadcast communication method. It was demonstrated to perform coordinated tasks, such as multi-target observation tasks. Major differences between this two behaviour-based systems include the need in ALLIANCE for motivational behaviours to store information about other individual robots, the lack of uniform inter-behaviour communication, and ALLIANCE's monitoring of time other robots have spent performing behaviours rather than BLE's local eligibility estimates. Similar to the above two architectures, many other researchers proposed and implemented many variants of behaviour-based architectures. Some of them used the classic three layer (plan-sequence-execute) approach, e.g., (Simmons et al. 2002) used a Layered Architecture where each layer interact directly to coordinate actions at multiple levels of abstraction.

Market-based architectures

Using the theory of marker economics and well-known Contract Net Protocol (CNP) (Davis & Smith 1988), these architectures solve the task-allocation problem by auction or bidding process. Major architectures following market-based approaches include MURDOCH (Gerkey & Mataric 2002), M+ system (Botelho et al. 1999), first-piece auction (Zlot et al. 2002), dynamic role assignments (Chaimowicz et al. 2002) among others.

Multi-agent based architectures

Some MRS architectures are influenced by multi-agent systems (MAS). For example, CHARON is a hierarchical behaviour-based architecture that rely on the notion of agents and modes. Similarly CAMPOUT is another distributed behaviour-based architecture that provide high-level functionality by making use of basic low-level behaviours in downward task decomposition of a multi-agent planner. It is comprised of five different architectural mechanisms including, behaviour representation, behaviour composition, behaviour coordination, group coordination and communication behaviours.

2.3.4 Interaction and learning

Interaction

According to the Oxford Dictionary of English the term interaction means reciprocal action or influence. In MRS research, such as in (Mataric 1994), interaction is referred to as mutual influence on behaviour. Following this definition, it is obvious that objects in the world do not interact with agents, although they may affect on their behaviour. The presence of an object affects the agent, but the agent does not affects the object since objects, by definition, do not behave, only agents do. However many other researchers acknowledge that interactions of robots with their environment (as found in stigmergic communication) have a great impact on their behaviours. Therefore, we adopt the broad meaning of interaction that is reciprocal action or influence among robots and their environment. From the above review of MRS system architecture, task allocation and communication, it is obvious that interaction among robots and their environment is the core of the dynamics of MRS. Without this interaction, it can not be a functioning MRS. While analysing the role and application of distributed intelligence on MRS, Parker (Parker 2008) presented an excellent classification of interactions of entities of MRS. She viewed the interactions along three different axes:

1. the types of goals of entities (either shared goal such as, cleaning a floor, or, individual goal)
2. whether entities have awareness of others on the team (either aware such as, in cooperative transport, or, unaware such as, in a typical foraging)
3. whether the action of one entity advances the goal of others (e.g., one robot's floor cleaning helps other robots not to clean that part of the floor)

Based on this approximate observation Parker classified interactions into four categories:

Collective interaction: Entities are not aware of others on the team, yet do share goals and their actions are beneficial to team-mates. Mostly, swarm-robotic work of many researchers follow this kind of interaction to perform biologically-relevant tasks, such as foraging, swarming, formation keeping and so forth.

Cooperative interaction: Entities are aware of others on the team, they share goals and their actions are beneficial to their team-mates. This type of interaction is used to reason about team-mates capabilities multiple robots works together, usually in shared workspace, such as cleaning a work-site, pushing a box, performing search and rescue, extra-planetary exploration and so forth.

Collaborative interaction: Having individual goals (and even individual capabilities), entities aware of their team-mates and their actions are beneficial to their team-mates. One example of this kind of interaction is a team of collaborative robots where each must reach a unique goal position by sharing sensory capabilities to all members such as illustrated as coalition formation in (Parker & Tang 2006).

Coordinative interaction: Entities are aware of each other, but they do not share a common goal and their actions are not helpful to other team members. For example, in a common workspace robots try to minimize interference by coordinating their actions as found in multi-robot path planning techniques, traffic control techniques and so on. Beyond this four most common types of interactions Parker also described another kind of interaction in adversarial domain where entities effectively work each other such as multi-robot soccer. Here entities have individual goals, they are aware of each other, but their actions have a negative affect on others goal.

Learning

A great deal of research on multi-robot learning has been carried out since the inception of MRS (Mataric 2001, Yang & Gu 2004, Parker 1995). Learning, identified as the ability to acquire new knowledge or skills and improve one's performance, is useful in MRS due to the necessity of robots to know about itself, its environment and other team-members (Mataric 2007). Learning can improve performance since robot controllers are not perfect by design and robots are required to work in an uncertain environment that all possible states or actions can not be predicted in advance. Besides learning a new skill or piece of knowledge it is also important to forget learned things that are no longer needed or correct as well as, to make room for new things to be learned and stored in a finite memory space of a robot.

Several learning techniques are available in robotics domain, such as reinforce or unsupervised learning, supervised learning and learning by imitation (Mataric 2007). Although reinforce learning, or learning based on environmental or peer feedback, is a good option for MRS, it has been found that in large teams the ability to lean in this way is restricted due to large continuous state and action space (Yang & Gu 2004). Several other learning techniques are also available to explore in MRS domain including Markov models, Q-learning, fuzzy logic, neural nets, game theory, probabilistic or Bayesian theory among others.

Based on a specific model of swarm behaviours researchers generally adopt similar communication methods to enable interaction of swarms as discussed in Section **??**. In (Balch 2005) three kinds of communication including, indirect stigmergic communication, direct robot to robot state communication, and goal communication were performed and it was found that in some tasks communication provided performance improvements while others did not. Since then, researchers emphasize on both the necessity and cost of communication in a swarm robotic system. Indirect communication approaches, e.g. virtual pheromone (Payton et al. 2005, Hamann & Worn 2006) by which mobile robots communicated through directional infrared messaging or LEDs, are mainly tried for large teams with the spatially distributed applications such as search and rescue, de-mining etc. More recently, (Cianci et al. 2007) reported a IEEE 802.15.4-compatible radio-communication module in e-puck robot for achieving multiple interactions simultaneously, as demonstrated in their collective decision making scenario. Although research on learning in swarm robotic teams was not explored widely, (Balch 2005) presented an example of reinforcement-based learning in multi-robot soccer and foraging tasks. He concluded that in a team of homogeneous robots with diverse behaviours, communication, interaction and learning are well interconnected and depending on the selection of global or local learning means, learning can be effectively employed in a swarm robotic system.

Conflict resolution

In MRS, conflicts occur if a resource is required by or, a unique single task is distributed to, more than one robot at any given time. Several resources such as bandwidth, space etc. may be needed by more than one robot. The space sharing problem was treated as traffic control problem in urban areas, but the robots are never restricted in road networks in case of behaviour-based control application (Cao et al. 1997). In explicit communication mode in MRS, the sharing of bandwidth among robots is a great problem in case of applications like multi-robot mapping (Konolige et al. 2003). In large multi-robot team such as in Centibots system (Ortiz et al. 2005), task interference and high bandwidth communication between 100s of robots appear as a significant research challenge.

2.3.5 Localization and exploration

Mobile robot systems highly rely on precise localization for performing their autonomous activities in indoor or outdoor. Localization is the determination of exact pose (position and orientation) with respect to some relative or absolute coordinate system. This can be done by using proprioceptive sensors that monitor motion of a robot or exteroceptive sensors that provide information of world representation, such as global positioning system (GPS) or indoor navigation system (INS). Many other methods are also available, such as landmark recognition, cooperative positioning and other visual methods.

Localization issue of MRS also invites researchers to examine specific areas like exploration and map generation. In exploration problem, robots need to minimize the time needed to explore the given area. Many researchers uses various kinds of exploration algorithms for solving this NP-hard problem, such as line-of-sight constrained exploration algorithm (Arkin & Diaz 2002), collaborative multi-robot exploration (Burgard et al. 2000) and so on. In mapping problem, mostly inaccurate localization information from teams of robots are accumulated and combined to generate a map by various techniques, such as probabilistic approaches (Thurn et al. 2000). Similar to in a MRS, localization is one of the hardest problem in swarm robotics. Without the presence of any centralized localization module, such as GPS or INS, it is not easy to localize precisely and locally the position of a robot with respect to other robots or environment. (Spears et al. 2006) presented a novel technique based on trilateration for localization of swarm robots using ultrasonic and RF transceivers without relying on global information from GPS, beacons, landmarks or maps. This system localize a robot with respect to other nearby robots and this is done using ultrasonic and RF signals. (Schmickl et al. 2006) reported hop-count and bio-inspired strategies for collective perception or how a swarm robot can join multiple instances of individual perception to get a global picture. Distributed mapping is another important application using swarms. (Rothermich et al. 2005) presented a collaborative localization algorithm using landmark based localization technique.

2.3.6 Applications of MRS

MRS systems have been put to numerous application domains that all can not be listed together. Rather than listing all of areas explored by researchers, below we have included few major areas that have received highest attention in the MRS research community. Sahin also listed a set of promising applications for swarm robots including spatially distributed tasks (e.g., environment monitoring), dangerous tasks (e.g., robotic de-miner), tasks that scale-up or scale-down over time, and tasks that require redundancy (Sahin & Spears 2005).

Object Transport

Cooperative transport of large objects (that one robot is unable to handle) by multi-robots was investigated by many researchers such as, following a formal model of cooperative transport in ants (Kube & Zhang 1993), box-pushing by six-legged robots (Mataric et al. 1995). Another kind of object transport problem include clustering objects into piles e.g., (Beckers et al. 1994), collecting waste or trash e.g., (Parker 1994), sorting coloured objects e.g., (Melhuish et al. 1998), constructing a building site collectively (**?**) and so on.

Mining

It has also been observed that multi-robot teams as micro or mini machines are helpful to improve the control and efficiency of mining and its processing operations (Dunbar & Klein 2002).

Military and Space Applications

Many researchers address MRS research issues under the requirements of a military or space application. Behaviour-based formation control (Balch & Arkin 1998), landmine detection (Franklin et al. 1995), multiple planetary rovers for various missions (Huntsberger et al. 2004) and so forth, all are the examples of this areas.

2.4 Task-allocation in MRS

Since 90s multi-robot task allocation (MRTA) is a common research challenge that tries to define the preferred mapping of robots to tasks in order to optimize some objective functions (Gerkey & Mataric 2004). Many MRS control architectures have been solely designed to address this task-allocation issue. In 2003 Gerkey et al. formally analysed the complexity and optimality of key architectures (e.g., ALLIANCE, BLE, M+, MURDOCH, First piece auctions and Dynamic role assignment) for this MRTA issue and it has been found that MRTA is an instance of the so-called optimal assignment problem (Gerkey & Mataric 2003) and generally known as NP-hard where optimal solutions can not be found quickly for large problems (Gerkey & Mataric 2004). If we look the MRTA problem from multi-agent system's perspective we can find it is broadly divided into two major categories (Shen et al. 2001):

1. Predefined (off-line) task-allocation and
2. Emergent (real-time) task-allocation.

Usually predefined task allocation method uses either centralized coordination or distributed task-allocation approach. Distributed predefined task-allocation approach is again subdivided into three subcategories:

1. Direct allocation,
2. Task allocation by delegation
3. Task allocation through bidding

In MRS domain, early research on predefined distributed task-allocation approach has been dominated mainly by intentional coordination (Gerkey & Mataric 2004, Parker 1998), the use of dynamic role assignment e.g., (Chaimowicz et al. 2002), and market-based bidding approach (Dias et al. 2006). In intentional coordination e.g., (Parker 1998), robots uses direct allocation method to communicate and to negotiate for assigning tasks. This is preferred approach among MRS research community since it is easily understood, easier to design, implement and analysis formally. Task allocation through bidding is mainly based on the Contract Net Protocol (Davis & Smith 1988). Predefined Task allocation through other approaches are also present in literature. For example, inspired by the vacancy chain phenomena in nature, (Torbjrn S. Dahl & Sukhatme 2003) proposed a vacancy chain scheduling (VCS) algorithm for a restricted class of MRTA problems in spatially classifiable domains.

On the other hand emergent task-allocation approach relies on the emergent group behaviours e.g., (Kube & Zhang 1993), such as emergent cooperation (Lerman et al. 2006), adaptation rules (Liu et al. 2007) etc., that lead to task allocation with local sensing, local interactions. It typically uses little or no explicit communication or negotiations between robots. They are more scalable to large team size and more robust via parallelism and redundancy.

MRTA problem can be addressed in many different ways depending upon the paradigm selected to abstract the problem and its relevant constraints and requirements (Parker 2008). Firstly, in emergent task allocation in bioinspired swarms paradigm MRTA homogeneous robots are employed to perform mostly similar tasks only by local sensing and indirect stigmergic (or no) communication. Secondly, in organizational and social paradigm MRTA can follow one of the two major approaches: 1) task allocation by making use of roles and 2) task allocation through bidding. For example, in multi-robot soccer, each role encompasses several specific tasks and heterogeneous robots select their roles based on their position and capabilities. In market-based approach, robots can negotiate with other team-mates to collectively solve a set of tasks. Finally, in knowledge-based approach, also known as intentional coordination, MRTA is done through the modelling of team-mate capabilities, such as by observing the performance of other team-members performance with or without explicit communication.

2.5 Communication in MRS

Communication between robots is an important issue in MRS (Arkin 1998). This is not a prerequisite for the group to be functioning, but often useful component of MRS (Mataric 2007). Let us now investigate why communication is important, how this is usually archived in MRS and related other issues.

Researchers generally agree that communication in MRS usually provides several major benefits, such as:

Exchange of information and improving 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.

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.

Enabling interactions: Communication is not strictly necessary for coordinating team actions. But communication can help a lot to interact (and hence influence) each-other in a team that, in turn, enables robots to coordinate and negotiate their actions.

Since a MRS can be comprised of robots of various computation and communication capabilities, it is also necessary to define the communication content and range (Arkin 1998, Mataric 2007). Usually robots can communicate about various states (e.g., task-related, individual, environmental etc.), their individual intentions and goals.

Robots communicate in a number of ways available under a specific application. This communication methods can be divided into two major categories:

Explicit communication: This is also known as intentional communication. This is done purposefully and usually using wireless radio. Based on the number of recipients of message, the communication process is termed differently. Such as, Broadcast communication: where all other robots receive the message. Peer-to-peer communication: where only a single robot receive the message. Publish-subscribe communication: where only a selected (previously subscribed) number of robots receive the message. 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 (loose of message) etc.

Implicit 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). Some researchers also tried to establish communication among robots through vision (Kuniyoshi et al. 1994).

In multi-robot communication researchers have identified several issues. Some of the major issues are discussed here. Kin Recognition Kin recognition refers to the ability of a robot to recognize immediate family members by implicit or explicit communication or sensing. In case of MRS, this can be as simple as identifying other robots from objects and environment or as finding team-mates in a robotic soccer. This is an useful ability that helps interaction, such as cooperation among team members.

Representation of Languages

In case of effective communication several researchers also focused on representation of languages and grounding of these languages in physical world.

Fault-tolerance, Reliability and Adaptation

Since every communication channel is not free from noise and corruption of messages significant attention has been also given to manage these no communication situations, such as by setting up and maintaining communication network, managing reliability and adaptation rules when there is no communication link available. In terms of guaranteeing communication, researchers also tried to find ways for a deadlock free communication methods (Arkin 1998), such as signboard communication method (Wang 1989).

Chapter 3

Experimental Tools

3.1 General Methodological Issues

3.1.1 Design of MRS

Before setting up a MRS platform for doing any practical research, one needs to decide the answers of a few basic questions. Firstly, what is the target application domain of this MRS ? Some MRS researches may try to implement and verify the performance of an algorithm inspired from biological social systems, while others may not. Some MRS may focus to solve real-life problems like emergency search and rescue in a disaster site, while others may concentrate on increasing productivity of a manufacturing shop-floor. The selection of this application domain will most likely determine the tasks to be done by individual or group of robots. This will lead to select suitable robots for doing that particular tasks. These tasks and robot group characteristics can be described by using any existing MRS taxonomies, e.g., taxonomies provided by (Gerkey & Mataric 2004) and (**?**) are widely used for this purpose.

Secondly, what are the organizing principles (i.e., control architecture) of the robot group in question ? From the task requirements and robot capabilities, one need to fit the MRS into a suitable paradigm of architecture and control. In Sec. 2.3 we reviewed three most common architectural paradigms of MRSs: classic knowledge-based, traditional market-based/role-based and bio-inspired swarm robotic paradigm. Upon selecting a paradigm, most important characteristics of target MRS: e.g., design of individual robot controller, robot-robot and robot-environment communication and coordination patterns etc. will be revealed.

Thirdly, what enabling tools and technologies (hardware and software) are required to function the whole robot group autonomously ? Whatever is the architectural design of a MRS, we need to ensure that whole group can maintain the necessary level of task performance through the desired interaction and communication strategies. For reducing cost and other practical reasons, individuals robots may not have the capabilities to localize itself without the help of an external GPS or camera etc. The enabling technologies will make-up this individual robot's shortcomings. Moreover, based-on a selected communication technology we need to set-up necessary robot-robot and robot-environment inter-networking infrastructure, e.g., network switches, gateways etc.

Finally, what extra hardware and software are necessary to observe and record experiments and its data for further analysis and improvement ? This extra system becomes an essential part of the target MRS.

We intend to design our target MRS for emulating multi-robot manufacturing scenario where robots do some shop-tasks in different machines. The notion of tasks has been kept very simple as our robots are not capable of doing many high-level practical tasks e.g. gripping or recognizing objects, carrying loads etc. Many researchers use additional hardware modules with their robots (e.g., gripper to collect pucks or any small objects from floors). We have not put any effort for emulating that kind of trivial activities, rather we concentrated on the performance of our algorithm, e.g. in task-allocation, from high-level perspectives. Doing real manufacturing tasks has been kept as a future research issue. Thus by "doing a task" our robots usually perform two functions: 1) navigate to a fixed task-location in the experiment arena (hereafter called *navigation*), and 2) they do so by avoiding any dynamic obstacle hereafter called *obstacle avoidance*. Depending on the time-out value of doing a task, a robot can wait at task-location if it arrives earlier or may switch to a different task and change direction on-the-fly. These symbolic tasks can be mapped to any suitable real task in multi-robot manufacturing domain, such as, material handling or attending a machine for various production or maintenance jobs e.g., welding different machine parts, cleaning or doing maintenance work of a machine etc.

Based on the task-requirements we have selected a simple miniature mobile robot, Epuck, that can do the above navigation tasks avoiding any dynamic or static obstacle. According to the classification of (**?**) our system can be described as:

`SIZE-INF:` The robot team size is larger than 2 robots and the number of the tasks. Actually we have kept the robot team size as multiple times larger than the number of tasks.

`COM-INF:` Robots can communicate with any other robot.

`TOP-ADD:` Every robot can communicate with any other robot by name or address (link path). Naming of robot's communication link path is assumed to follow any simple convention, e.g., /robot1, /robot2 etc.

`BAND-INF:` Every robot can communicate with other robot with as much bandwidth as necessary. Since our robots need to exchange simple messages we ignore this bandwidth issue.

`ARR-DYN:` Robot can change the arrangement dynamically.

`CMP-HOM:` Each robot is initially identical in both hardware and software, but they can become different gradually by learning different tasks by different degrees (in software).

We have closely followed the swarm robotic principles for controlling the group. Although we do not impose any necessity for local communication and interaction. The details of our control architecture has been described in Sec. expt-tools:arch. Since our robots can not localize themselves by their own hardware we provided them their instant position and orientation (hereafter called *pose*) data information from a multi-robot tracking system (MRTS). Sec. 3.3.1 describes about our tracking system. This system also helps us in recording and logging individual robot's task performance and pose information. We use Bluetooth communication technology, built-in with our E-puck robots, for host PC to robot communication. Robot can also communicate with each-other physically over Bluetooth. However, we do not use that mode of communication. Instead, inter-robot communication is done in host PC's virtual inter-process communication channel. This has been illustrated in Sec. 3.3.1.

3.1.2 Real robot experiments – No simulation

Traditionally robotic researchers use software simulation to validate their model before stepping into real-robot experiments. Simulating a model by software code is easier and much faster compared to real-world experiments. It does not require any sophisticated hardware setup or time-consuming debugging. However, in modern times the abundance of real hardware systems and tools encourage researchers to test their work in real systems from the inception of their models. Here we briefly summarize the reasons why we do not follow the traditional "simulation first" approach. Instead of comparing both approaches extensively, we present our rationale behind doing all our experiments in real hardware.

Firstly, contemporary state-of-the-art agent-based simulation packages are essentially discrete-event simulators that execute models serially in a computer's CPU (**?**). However in real-world systems agents act in parallel and give us the "what you see is what you act upon" environment. In simulations that might not be case.

Secondly, the robot-robot and robot-environment interactions are complex and completely unpredictable than their simulations. Unexpected failures and inter-agent interactions will not occur in simulations that can either cause positive or negative effects in experimental results (Krieger & Billeter 2000).

Thirdly, it is not easy to faithfully model communication behaviours of agents in simulations. In our case, we use short-range Bluetooth communication system which is subject to dynamic noise and limited bandwidth conditions.

Fourthly, the dynamic environment conditions, e.g., increased physical interferences of larger team of robots, can also influence the experiment's outcome which is obvious in simulations.

Finally, we believe that the algorithm tested in real-robots can give us strong confidence for implementing in real-systems and later on, this can also be extended or verified in simulations. However, conversely speaking, algorithm implemented in simulation has no warranty that this will work practically with robots.

3.2 Hardware

3.2.1 E-puck robots

We use E-puck [1] robots developed by Swiss Federal Institute of Technology at Lausanne (EPFL) and now produced by Cyberbotics [2] and some other companies. The upside of using E-puck is: it is equipped with most common sensing hardware,

[1] www.e-puck.org
[2] http://www.cyberbotics.com

Table 3.1: E-puck robot hardware

Feature	**Description**
Diameter	about 7 cm
Motion	max. 15 cm/s speed (2 stepper motors)
Battery power	about 3 hours (5Wh LiION rechargeable battery)
Processor	16 bits micro-controller with DSP core, Microchip dsPIC 30F6014A at 60MHz (about 15 MIPS)
Memory	RAM: 8 KB; FLASH: 144 KB
IR sensors	8 IR sensors measuring ambient light and proximity of obstacles in a range of 4 cm
LEDs	8 red LEDs on a ring and 1 green LED in the body
Camera	colour camera (max. resolution of 640x480)
Sound	3 omni-directional microphones and on-board speaker capable of playing WAV or tone sounds
Bluetooth	for robot-computer and robot-robot wireless communication

relatively simple in design, low cost, desktop-sized and offered under open hardware/software licensing terms. So any further modification in hardware/software is not limited to any proprietary restriction. However, the downside of using E-puck robot is: it's processor is based on dsPIC micro-controller (lack of standard programming tool-chains), limited amount of memory (lack of on-board camera image processing option) and default communication module is based-on Bluetooth (limited bandwidth and manual link configuration). So the programming of E-puck can be done through C language and uploaded from PC to robot through wire: I^2C and RS232 channel or, through Bluetooth wireless communication channel. This can be tedious and time-consuming if one needs to change the robot controller frequently. However, we intend to keep the robot's functionalities very simple and limited to two main tasks: avoiding obstacles and navigating from one place to another. Thus the default hardware of E-puck seems enough for our experiments.

Table 3.1 lists the interesting hardware information about an E-puck robot. The 7 cm diameter desktop-sized robot is easy to handle. It's speed and power autonomy is also reasonable compared with similar miniature robots such as Khepera and its peers (**?**). The IR sensors provide an excellent capabilities for obstacle avoidance task. Although we do not make use of the tiny camera of E-puck, the combination of sound and LEDs can be very effective to detect low-battery

Table 3.2: Features of Prosilica GigE Camera GE4900C

Feature	**Description**
Type	Charge-coupled device (CCD) Progressive
CCD Sensor	Kodak KAI-16000
Size (L x W x H)	66x66x110 (in mm)
Resolution	16 Megapixels (4872x3248)
Frame rate	Max. 3 frames per second at full resolution
Interface	Gigabit Ethernet (cable length up to 100 meters)
Image output	Bayer 8/12 bit

power or any other interesting event. By default, E-puck is shipped with a basic firmware that is capable of demonstrating a set of it's basic functionalities. Using the supplied Bluetooth serial communication protocol (hereafter *BTCom protocol*), it is possible to establish serial communication link between host PC and robot firmware at a maximum possible speed of 115 kbps. Using this protocol, one can remotely send command to robot, e.g., set the speed of the motors, turn on/off LEDs and read the sensor values, e.g., read the IR values or capture image of the camera etc.

3.2.2 Overhead GigE camera

In order to set-up a multi-robot tracking system (MRTS), we have selected a state-of-the-art GE4900C colour camera from Prosilica [3]. The Prosilica GE-Series camera, are very compact, high-performance machine vision cameras with Gigabit Ethernet interface. This has following main features:

CCD technology convert light into electric charge and process it into electronic signals. Unlike in a complementary metal oxide semiconductor (CMOS) sensor, CCD provides a very sophisticated image capturing mechanism that gives high uniformity in image pixels. The high resolution enables us to track a relatively large area e.g., 4m X 3m. In this case, 1 pixel dot in image roughly can represent approximately 1mm X 1mm area. Although the frame rate may seem low initially, but this small frame-rate gives optimum image processing performance with large image sizes, e.g. 16 MB/frame. Prosilica offers both Windows and Linux SDK for

[3]http://www.prosilica.com

Table 3.3: Server PC Configuration

Processor	Quad-Core Intel Xeon Processor up to 3.33GHz (1333MHz FSB, 64-bit, 2X 6MB L2 cache)
RAM	32GB (4GB ECC DIMMS x 8 slots)
Graphics Card	NVIDIA Quadro FX 570 (Memory: 256MB)
Hard-disk	SATA 3.0Gb/s 7200RPM 2 x 250 GB
OS	Ubuntu Linux 9.10 64bit

image capture and other necessary operations. Using this SDK, we have converted default Bayer8 format image into RGB format image and used that in our tracking software.

3.2.3 Server PC Configuration

We use Dell Precision T5400 server-grade PC with the following main technical specifications: This high performance PC has supported us implementing our algorithms without having any fear of running out of RAM. Since the maximum supported RAM of a 32 bit PC architecture is limited to 2 GB we select Ubuntu Linux 9.10 64bit OS. As an open-source OS, Ubuntu offers excellent reliability, performance and community support. In order to enable Bluetooth communication in our host PC, we have added 8 USB-Bluetooth adapters (Belkin F8T017) through a suitable USB-Bluetooth hub.

3.3 Enabling Software Tools and Frameworks

3.3.1 SwisTrack: A Multi-robot Tracking System

3.3.2 D-Bus: An Inter-Process Communication Protocol

3.3.3 BTCom/Myro: E-puck Robot Control Programs

3.3.4 Bluez: Linux's Bluetooth Communication Stack

3.3.5 Python's Multiprocessing: Multi-Threading Made-easy

3.4 Multi-robot control architecture

3.4.1 Three-layered event-driven hybrid control

3.4.2 D-Bus inter-process communication

3.4.3 Robot controller client

3.4.4 Task perception assistant

3.4.5 Integration with Python multiprocessing

3.4.6 Distributed deployment of software components

Chapter 4

Attractive Field Model for Self-regulated Task Allocation

4.1 Inter-disciplinary motivations

4.2 General characteristics of AFM

AFM provides an abstract framework for self-regulatory DoL in social systems (**?**). In terms of networks, the model can be constructed as a bipartite network, meaning that 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. The links only take place between different types of nodes, and these encode the flow of information. So even if there is no direct link between two agents, their interaction is taken into account in the information flow. The dependence of the strength of the field on the distance can be represented in terms of networks through weighted links. In addition, there is a permanent filed. It comes from the no-task option of ignoring the information. The model can be mapped to a network as shown in Fig. **??**. The correspondence is given below:

- Source nodes (o) are tasks that can be divided between a number of agents.
- Agent nodes (x) are robots.
- The attractive fields correspond to stimuli to perform a task, and these are given by the black links.
- When an agent performs a task, the link is of a different sort, and this is

denoted in the figure by a red line. Agents linked to a source by a red line are the robots currently doing that task.

- 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 green lines in the graph.
- 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. In addition, 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, the nodes have an arbitrary place. 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, looking at the network, we see that each of the agents is connected with a link 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 different from zero. So the weighted links express the probability of an agent to be attracted to each of the fields.

4.3 Interpretation of AFM for MRS

AFM provides us a generic framework for implementing self-regulatory MRTA. Here we briefly describe how this model gives our robots self-regulatory behaviours, particularly task-specialization, concurrency, flexibility and robustness. Interested readers should consult (**?**) for a general overview and (**?**) for our robotic implementation of AFM. Let us consider a manufacturing shop floor scenario where N number of mobile robots are required to attend to M number of shop tasks spread over a fixed area A. Let these tasks be represented by a set of small rectangular boxes resembling to manufacturing machines. Let each task j has an associated task-urgency ϕ_j that indicates its relative importance over time. If a robot attends to a task j in xth time-step, value of ϕ_j will decreases by a small amount, $\delta_{\phi 1}$ in (x+1)th time-step. On the other hand, if a task has not been served by any robot in xth time-step, ϕ_j will increase by another small amount, $\delta_{\phi 2}$ in (x+1)th time-step. In order to complete a shop task j, a robot needs to reach within a fixed boundary of j, D_j. If a robot completes a task j we say that it learns about it and this will increase robot's likelihood of selecting that task in next step. We call this variable affinity of a robot to that task as its sensitization k_j. If a robot does not do a task j for some time, we say that it forgets about j and k_j has been decreased.

According 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 called stimulus will vary according to the distances between robots and tasks, task-urgencies and corresponding sensitizations of robots. This is encoded in Eq. 4.1.

$$S_j^i = tanh\{\frac{k_j^i}{d+\delta}\phi_j\} \qquad (4.1)$$

$$P_j^i = \frac{S_j^i}{\sum_j S_j^i} \qquad (4.2)$$

Eq. 4.1 states that the stimuli of a robot i to a particular task j, S_j^i depends on robot's spatial distance d to j, level of sensitization to that task (k_j^i) and perceived urgency of that task (ϕ_j). We use a vary small value δ in Eq. 4.1 to prevent division by zero. The probability of selecting each task has been determined by a probabilistic method outlined in Eq. 4.2 (**?**). AFM ensures concurrency of a self-regulatory system by specifying at least two task options: 1) doing a task and 2) doing no task. In robots, the latter can be be treated as random walking. So in any time-step a robot will choose from M+1 tasks. Let T_a be the allocated time to accomplish a task. If a robot can enter inside the task boundary, r_{task} within T_a time it waits there until T_a elapsed. Otherwise it will select a different task.

4.4 AFM under centralized communication system

4.5 Robotic validation of AFM

4.5.1 Experiment design

4.5.2 Robot controller implementation

4.5.3 Task perception assistant implementation

4.5.4 Experiment setup: centralized communication mode

4.5.5 Results

4.5.6 Discussions

4.6 Summary and conclusions

Chapter 5

Scale-free Multi-robot Task Allocation with AFM

5.1 Scale-free properties

5.2 Scale-free experiments

5.2.1 Experiment design

5.2.2 Experiment setup: centralized communication mode

5.2.3 Results

5.2.4 Discussions

5.3 Summary and conclusions

Chapter 6

Locality-based Decentralized Communication Model

6.1 Biological motivations

6.2 Geometrical analysis

6.3 General characteristics

Our communication model relies on the local P2P communications among robots. Here there is no centralized server to disseminate information but each robot can communicate to its nearby peers within a certain communication radius, r_{comm}. Here by r_{comm}, we assume that within this distance robots can exchange communication signals reliably without any significant loss of information. A robot R_1 is a *peer* of robot R_2, if spatial distance between R_1 and R_2 is less than its r_{comm}. As shown in Fig. **??**, local communication can also give robots similar task information as in centralized communication mode. It shows that it is not necessary for each robot to communicate with every other robot to get information on all tasks. Since robots can random walk and explore the environment we assume that for a reasonably high robot to space density, all task will be known to all robots after an initial exploration period. In order to update the urgency of a task, robots can estimate the number of robots working on a task in many ways: such as, by using their sensory perception (e.g., camera), by doing local P2P communication and so on. In Fig. **??** we have shown that robots exchange both task information and self status signals to peers.

We characterize our communication model in terms of three fundamental issues: 1) message content (*what to communicate*) 2) communication frequency (*when to communicate*) and 3) target recipients (*with whom to communicate*) (**?**). In a typical MRS, message content can be categorized into two types: 1) state of each individual robot and 2) target task (goal) information (**?**). The latter can also be subdivided into two types: 1) an individual robot's target task information and 2) information of all available tasks found in the system. Regarding the first issue, our communication model is open. Robots can communicate with their peers with any kind of message. Our model addresses the last two issues very specifically. Robots communicate only when they meet their peers within a certain communication radius (r_{comm}). Although in case of an environment where robots move relatively faster the peer relationships can also be changed dynamically. But this can be manipulated by setting the signal frequency and robot to space density to somewhat reasonably higher value. In terms of target recipients, our model differs from a traditional publish/subscribe communication (PSC) model by introducing the concept of dynamic subscription. In a traditional PSC model, subscription of messages happens prior to the actual message transmission. In that case prior knowledge about the subjects of a system is necessary. But in our model this is not necessary as long as all robots uses a common addressing convention for naming their incoming signal channels. In this way, when a robot meets with another robot it can infer the address of this peer robot's channel name by using a shared rule. A robot is thus always listening to its own channel for receiving messages from its potential peers or message publishers. On the other side, upon recognizing a peer a robot sends a message to this particular peer. So here neither it is necessary to create any custom subject namespace (e.g., (**?**)) nor we need to hard-code information in each robot controller about the knowledge of their potential peers *a priori*. Subscription is done automatically based on their respective r_{comm}.

6.4 Implementation algorithm

Our local communication model has three major aspects: 1) local sensing of peers (and optionally tasks), 2) listening to peer signals and 3) emitting signals for peers. Here we present a typical implementation. Let N be the set of robots. At time step q, a robot i that can receive $h_{i,q}$ information by listening to its incoming channel L_i. Let M be the set of tasks. Each task j has an associated information H_j. It encodes the necessary properties of tasks, such as their locations, urgencies etc. Each task j also has a task perception radius r_{task} such that if a robot comes within this radius at time step q it can perceive current value of $H_{j,q}$. Let at time step q, robot i has its own task information $G_{i,q}$ that has been perceived and listened from its peers. Let r_{comm} be the communication radius of each robot. Let at time step q, $P^i_{p,q}$ be a set of peers of i that are within r^i_{comm}. Let $E^i_{p,q}$ be its active signal emission channels. Algorithm 1 implements our proposed dynamic P2P communication.

Algorithm 1: Locality based Dynamic P2P Communication

Initialization:
$id \leftarrow robotid$
$r_{comm} \leftarrow r_1$
$r_{task} \leftarrow r_2$
$pose[id] \leftarrow (0,0,0)$
$G[id],\ P[id],\ L[id],\ E[\,] \leftarrow 0$
Loop:
$pose[id] \leftarrow (x,y,\theta)$
if $pose[id] \in U(pose[k],\ r^k_{task}), (k = 0,1,.,M-1)$ **then**
    $G[id] \leftarrow G[id] \cup H_k$
end if
if $pose[id] \in V(pose[k],\ r^k_{comm}), (k = 0,1,.,N-1, k \neq id)$ **then**
    $P[id] \leftarrow P[id] \cup k$
    $h_k \leftarrow W(E[k],\ L[id])$
    $G[id] \leftarrow G[id] \cup h_k$
end if
for all $k \in P[id], (k = 0,1,.,N-1, k \neq id)$ **do**
    $W(E[id],\ L[k]) \leftarrow G[id]$
end for
$P[id] \leftarrow 0$
Loop again

From Algorithm 1, we see that a robot controller is initialized with its specific robot-id and default values of r_{comm} and r_{task}. We assumed that these values are same for all robots and for all tasks respectively. Initially a robot has no information about tasks. It has neither listened nor transmitted any information yet. Upon initialization, robot determines its current pose and evaluates a function $U(pose,\ r_{task})$ that helps it to perceive information of a nearby task. This is not strictly necessary as this information can be available from alternate sources. In second step, robot senses its nearby peers by evaluating $V(pose,\ r_{comm})$ and start filling the list of peers P by their id. The signal exchange with a peer is denoted by a communication function $W(emitter,\ listener)$. So by listening to a peer signal, it receives task information h and aggregates this h with its own task info G. In last step, robot emits its task information to its peers stored in P. Finally it erases all values of P and repeat this loop.

6.5 AFM under local communication system

6.6 Locality based decentralized communication experiments

6.6.1 Experiment design

6.6.2 Robot controller implementation

6.6.3 Task perception assistant implementation

6.6.4 Experiment setup: local communication mode

6.6.5 Results

6.6.6 Discussions

6.7 Summary and conclusions

Chapter 7

Conclusions

7.1 Summary of contributions

7.2 Future work

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