Chapter 7

Deployment and Redeployment of Wireless Sensor Networks: a Swarm Robotics Perspective

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Abstract. *Deployment of WSNs is an important issue that requires careful consideration, as it can make the difference between an efficient and an unproductive system. The introduction of node mobility provides a wealth of potential solutions to the deployment problem, which can lead to higher robustness, flexibility and adaptivity. When provided with mobility features, network nodes are analogous to autonomous robots with local sensing and communication abilities. Therefore, behavioral strategies developed for collections of autonomous robots may be exploited in the mobile WSN domain. This is particularly true for swarm robotics studies, which emphasize self-organizing behaviors that deal with limited individual abilities, local sensing and local communication. In this chapter, we discuss the challenges and opportunities offered by swarm robotics with respect to the deployment of mobile WSNs. We review the state of the art in swarm robotics for coverage, exploration and navigation tasks, which are directly linked to the deployment problem, and we identify relevant directions for an hybridization of WSN and swarm robotics research.*

7.1 Introduction

The deployment of a wireless sensor network is a relevant issue that can have a strong impact on the system efficiency and on the quality of service. Speaking in general terms, any given application may have specific deployment requirements that have to be met to optimize the network performance, preventing the usage of a priori generic strategies for deployment, and requiring flexible and adaptable methods [44].

Fixed deployment strategies may be unpractical for the application domain or too costly, for instance in case of harsh environmental conditions that do not allow precise positioning of sensors. The requirements for deployment may also vary in time, either due to application-specific demands or to variability in the network operating conditions (e.g., failure of some nodes). As a consequence, research in WSN deployment has often postulated the need of mobile sensors capable of positioning themselves starting from a deployment site, or capable of repositioning after an initial coarse deployment (e.g., launch from a plane). In this context, a number of different studies can be found, in which distributed deployment algorithms are proposed to obtain a desired distribution of sensors in the environment [1, 2, 13, 20, 27, 41, 45].

As soon as mobility comes into the game, sensor nodes become more and more similar to autonomous agents that decide their motion according to the environmental contingencies they experience, both related to the mission (i.e., the phenomenon to be monitored) and the network itself (i.e., the neighboring nodes and their operating conditions). If we exclude minimalistic mobility features, such as spring-propelled nodes capable of a single flip [7], mobile nodes can be surely considered autonomous robots with their sensing and motion capabilities. Alternatively, autonomous robots can be exploited to move sensor nodes to a desired location [6, 26, 37]. In both cases, the particular context of mobile WSNs naturally lends itself to a parallel with swarm robotics systems. Indeed, mobile WSNs and swarm robotics systems share the same foundational characteristics: large number of nodes/agents, local sensing and communication, limited individual sensory-motor and processing capabilities. It is therefore interesting to look at the swarm robotics literature to draw a parallel between the approaches exploited in swarm robotics related to coverage, exploration and navigation, as they can give novel solutions for the WSN domain, either inspiring novel algorithms for mobile nodes, or by providing robotic solutions for the automatic deployment, replacement and redeployment of (immobile) sensor nodes. In this chapter, we will examine the swarm robotics literature and will draw a parallel among swarm robotics and WSN algorithms. In Section 7.2, we discuss the specific challenges and opportunities offered by swarm robotics, with particular reference to the problems faced in the context of WSNs. In Section 7.3, we review the state of the art in swarm robotics discussing the most advanced solutions for problems of coverage, exploration and navigation. In Section 7.4, we discuss possible applications of swarm robotics approaches to the WSN domain, as well as cross-fertilization between the two. Section 7.5 concludes the chapter.

7.2 Challenges and Opportunities Offered by Swarm Robotics

Swarm robotics is a specific approach in the design and control of distributed multi-robot systems, which is characterized by a strong emphasis on self-organization as the main way to obtain desired system properties, such as scalability, flexibility and robustness. As mentioned above, swarm robotics systems are relatively large in the number of robots, which goes from few tens to many hundreds. Each robot is completely autonomous in its control, and behaves according to simple rules of thumb based on local sensing and local communication with neighboring agents. Decentralization of control and locality of available information make the design of swarm robotic systems particularly challenging, because it is necessary to identify which can be the locally-executed control rules that will lead to a desired global behavior. More specifically, the design problem is created by the indirect, often non-linear relationship between the individual behavior and the swarm organization. This makes it difficult to predict what is the macroscopic effect of microscopic control rules usually performed only with partial and noisy information.

An important assumption that characterizes swarm robotics systems is the lack of absolute positioning information. Normally, robots do not mount GPS receivers to provide a location estimate. Neither other absolute localization and tracking techniques are envisaged for robot control (e.g., the Vicon system[1]). Indeed, swarm robotics systems are intended for unstructured environments where the absence of any infrastructure is compensated by the cooperative action of a large number of robots. In this perspective, potential applications are search and rescue in disaster areas, space exploration or underseas monitoring. The lack of absolute positioning represents the bigger difference between swarm robotics and the mobile WSN domain. In mobile WSNs, motion of the nodes is (locally) planned on the basis of an absolute reference frame and the absolute position of neighboring nodes, and distributed algorithms are deployed with predictable properties that are often based on the availability of positioning

[1] http://www.vicon.com

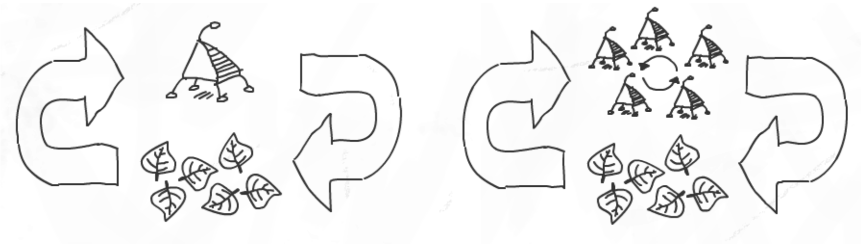

Fig. 7.1 A pictorial description of the sensory-motor loop. Left: a robot in interaction with the environment. In the single robot case, the action of the robot is executed in the environment, and the new environmental situation is perceived through the robot sensors. Right: in the swarm robotics case, multiple robots act at the same time and determine the state of the environment as it will be perceived by their sensors. Additionally, robots communicate and interact among themselves.

information. The challenge that is given by the relaxation of the localization assumption requires that the motion planning be performed in a local reference frame, on the basis of the communication with neighboring nodes. In these conditions, swarm robotics offers several algorithms that could be directly translated to the WSN domain, as we will see in Section 7.3.

Another assumption that is often made in WSNs and that is instead relaxed in swarm robotics systems concerns the maintenance of a global connectivity among the nodes. Indeed, disconnected nodes in a WSN are of no use for the application in place. This is why the maintenance of connectivity is one of the first properties to check in a distributed algorithm for mobile sensors. In swarm robotics, instead, the autonomy of the individual robots in executing their behavior allows them to continue working even when connection with other robots is (temporarily) lost. The higher mobility of robots with respect to mobile sensors and the possibility of dead-reckoning thanks to proprioceptive sensors (i.e., wheels encoders) make robotic systems more flexible and versatile. Still, when deployed in open environments and harsh environmental conditions (e.g., underseas), the maintenance of connectivity is an important challenge to be faced.

The ability to recover connectivity when lost is also supported by fast sensory-motor loops which normally characterize the autonomous robots behavior. In this respect, robots are different from mobile sensors in the fact that the behavior is the result of a fine-grained succession of actions and sensations. This is particularly true for reactive behaviors, such as those usually implemented in swarm robotics systems. In this case, the behavior performed by an individual robot often follows simple rules, that is, an action is chosen principally on the basis of the current sensory perception (plus some internal state information), and the executed action partially determines the following perceptual state in which the robot will find itself, therefore starting a novel sensory-motor loop (see Figure 7.1 left). Controlling a robot at such a fine-grained level is a challenging task, but this also offers the opportunity to exploit fast control loops to recover from errors and adapt to the environmental contingencies at hand. In the swarm robotics context, it is the whole swarm that rapidly changes state, and this has a bearing on the flow of perceptions that each individual robot experiences. Additionally, direct communication between robots must be taken into account to determine the action to be performed (see Figure 7.1 right). Therefore, controlling a robot within a swarm is challenging because the sensory state of a robot is not only determined by the action just performed, but it depends on the actions and state of the (possibly many) neighboring robots. An important challenge is however accompanied also by great opportunities, as the complexity of the behavior exhibited by a swarm goes far beyond the individual capabilities. A swarm can display quick information spreading and collective responses that are faster than the individual reaction times. It can take decisions without any single individual testing more than a single alternative. More generally, a swarm robotic system can behave optimally despite the inability of individual robots to acquire a global picture of the problem.

The above considerations summarize some of the most relevant differences between the domains of swarm robotics and of WSNs. Nevertheless, as mentioned in the introduction, it is worth making a parallel between these two domains, as cross-fertilization may provide a leap forward for both. In the following section, we therefore review the swarm robotics literature and discuss the relevant work that resonate with the problems faced in deployment and redeployment of mobile WSNs.

7.3 Current Approaches in Swarm Robotics

There is a large number of studies that can be considered in the attempt to look at the problems faced in WSNs from a swarm robotics perspective. We have decided to limit our investigation to exploration and navigation problems. In these activities, a swarm must search a given area of interest, either by covering it in all its parts or by focusing in precise points of interest, connecting them to some 'home' location. In all the studies presented below, the system has to deal with the absence of an absolute positioning system and of a common reference frame. Control is completely distributed and robots normally execute very simple individual behaviors. Coordination and cooperation among robots is generally required in order to cope with these limitations. We classify the swarm robotics studies in three main approaches: (i) coverage, (ii) chain formation, and (iii) communication assisted navigation. In the following sections, we give a generic description of the specific approach, and then we review the relevant work within it.

7.3.1 *Coverage in swarm robotics*

In swarm robotics, coverage refers to the problem of deploying a swarm of robots with the dual goal of maximizing the covered area and of keeping neighbors in communication range to keep the network fully connected. The first to define this problem has been discussed in Gage [14]. Coverage can have various scopes that we categorize in two main classes: *surveillance* and *navigation*. In both problems, a swarm of robots with limited sensing capabilities has to spread over a wide area. To compensate for the limited capabilities of individual robots, the swarm organizes in a network that fully covers the environment to detect possible changes or anomalies and keeps communication between nodes to spread information. In surveillance problems, the network itself carries out the desired task monitoring the environment; differently, in navigation, the resulting network is a support structure for aiding other agents (e.g., robots or humans) to complete their task. In this case, the resulting network is exploited by other agents to localize and to move in environments where unassisted navigation might be challenging, e.g., unknown or dynamic environments.

Several solutions to this problem have been proposed. We classify them according to the deployment method. We identify two main classes: artificial force based and incremental deployment.

Artificial force based. Methods based on artificial forces consider each robot as an embodied particle which exerts virtual forces on other robots. The motion of each individual robot is controlled by the resultant virtual force imposed by its neighboring robots and other components of the system. After a certain period, the system converges towards an equilibrium state in which the forces between robots are minimized. This virtual force is calculated on-board by each robot in a distributed and asynchronous way.

Additionally, this approach does not require models of the environment, localization, or communication between nodes. The only requirement is that the robots can perceive the relative position of the other robots in a local range. As a result, the algorithm is highly scalable. A further positive characteristic of this method is its simplicity, as the robots use a single mathematical rule to translate the sensor readings into a movement vector. As advantage, the behaviors written using this design method are robust and can be easily combined with vectorial operators. Finally, considering robots as particles subjected to external forces allows the developer to analyze the systems and to prove its properties with theoretical tools borrowed from solid scientific areas such as physics, control theory or graph theory [15].

The seminal work in this area is by Genovese et al. [16]. They propose a redeployment method for robotic sensor networks based on artificial forces of attraction and repulsion. The goal is to obtain a distribution of the robots proportional to the density of a pollutant in the environment, that is, a higher density of robots in more polluted areas. The robots are equipped with sensors that allow them to detect the pollutant concentration and the gradient direction. The robot movement is the result of the attraction towards higher pollutant densities (based on the gradient ascent) and repulsion from other robots.

Some years later, Reif and Wang [32] proposed the *social potential field*. In their work, each robot is subject to an artificial force, which is either attraction or repulsion from other robots according to the distance that separates them. The artificial force attracts towards robots further than distance d and repulses when the distance is smaller than d. The authors propose a set of heuristics to design social potential fields for achieving a variety of behaviors like clustering, covering, patrolling, etc. In the case of coverage, it is sufficient to fix the distance d as the limit of the communication range. In this way the robot formation maximizes the coverage while keeps connectivity between the robots of the swarm. A similar work of diffusion with artificial potential field force has been proposed three years later by Howard et al. [23].

Payton et al. [30] propose a coverage behavior implemented with similar attraction/repulsion forces. In this work, a part of the robots take static positions in the environment, acting as landmark to support the navigation of the other robots in the environment. Poduri and Sukhatme [31] study the coverage problem with the additional constrains of keeping a minimum number K of neighbors for each node. Their solution is based on varying the parameterization of the two forces (attraction and repulsion) in function of K. Spears et al. [34] introduce a general framework for physics-based behavior design, called *physicomimetics*. The authors also provide analytical studies of the potential energy and force balance equations. This novel artificial physics analysis provides a system parameterization technique to design networks with the desired topology. The framework is validated through a set of real robot experiments. Zavlanos and Pappas [46] provide a theoretical framework for controlling graph connectivity in mobile robot networks. By applying this framework to distributed algorithms, they study how to maintain, increase, and monitor connectivity in mobile robot networks. Vail and Veloso [39] apply a coverage method, based on artificial potential field, for RoboCup controllers. The work of Kalantar and Zimmer [25] proposes a decentralized method to the deployment of autonomous underwater vehicles. The work focuses on the coverage of specific areas of arbitrary shape, but known in advance. The proposed method is composed of various distinct phases, during which the robots interact locally to achieve the dual goal of covering the interior of the target area with an uniform distribution and of creating the formation border as similar as possible to the desired shape. The solution is based on virtual forces of attraction and repulsion, which are varied during the different phases of the process. The method is evaluated through a set of simulation experiments.

In conclusion, artificial force based methods, although simple, have shown to be suitable for a wide range of robot network applications. The systems implemented using these methods are fully decentralized, robust, scalable and require minimal sensing capabilities of the robots.

Incremental deployment. Incremental deployment algorithms position nodes one-at-a-time in an unknown environment, with each node determining its target location exploiting the previously deployed nodes. The network can either support the deployment of new nodes furnishing localization information or directly navigating them to their target positions.

Howard et al. [22] propose an incremental deployment algorithm for groups of homogeneous mobile sensors having as goal to maximize the network coverage and as constraint to maintain full connectivity. Each sensor calculates its target position by collecting all the maps generated by the already deployed nodes, merging them, and using the generated global map to calculate its position.

While the Howard's work is based on homogeneous mobile sensors, Tang et al. [38] exploit the heterogeneity of the devices: mobile sensor nodes with very limited navigational capabilities are guided to their deployment positions by more intelligent *leader* robots. Only a limited set of devices (the leaders) has capabilities to localize themselves in the (known) map, while the others are mere followers navigated to their positions. In the proposed system, as first phase, an off-line global-knowledge planner calculates the desired deployment positions of the sensors and of the leader robots, which are used as way-points during the actual deployment process. As second phase, a small team, of about 5 mobile sensors, is assigned to each leader which navigates them to preplanned positions. Iteratively, the leaders return to the base station to recruit other teams to be deployed. The navigation of the leader in the environment is facilitated by the already deployed sensors. This work has been extended by Howard et al. [24] adding to the algorithm an initial phase of exploration performed by the leader robots, which generate a global map of the environment subsequently used to plan the deployment positions. The work includes a series of experiments with real robots involving 3 leaders and 35 followers.

Stirling et al. [36] propose a fully-distributed strategy to coordinate a swarm of flying robots for indoor deployment and dynamic redeployment with particular attention on energy efficiency. Also this method is based on an incremental deployment to gradually expands the robot sensor network. Differently from the previous works, the approach is totally decentralized, does not require any reconstruction of the map, nor any exchange of large amounts of data nor any global-positioning system, but rather it relies only on relative-positioning sensors. This makes the presented algorithm scalable, with low computational complexity for any environment and swarm size.

Other methods. The following works present coverage algorithms that do not implement any of the two methods presented above. However, these works propose decentralized solutions of interesting coverage problems which are worth to be mentioned.

Winfield [43] proposes a distributed method for coverage of large environments with not sufficient resources. The robots have limited sensing and communication range, and the physically bounded environment is assumed to be sufficiently large such that cannot be entirely covered by the full connected robotic network. To overcome this constraint, the proposed solution exploits the mobility of the robots, which keep moving in the arena. The robot random motion brings them in contact, and lets the information propagate within the network.

Batalin and Sukhatme [4] compare an artificial force method based on only repulsion force with a simple rule-based local dispersion algorithm. The two investigated approaches provide similar performances.

Subsequently, the rule-based algorithm has been modified ([3]) to let mobile robots deploy small communication beacons in an unknown environment. These beacons are exploited by the robots to perform exploration of the environment.

Schwager et al. [33] present a decentralized, adaptive algorithm to deploy a network of mobile robots to an optimal sensing configuration. The sensing network has the double goal of spreading out and of maximizing the sensing metrics through aggregation in areas of high interest. The robots do not know in advance where these areas are, but they estimate this information on-line from sensor measurements. In this way, the system is decentralized and adaptive to environmental changes. Each robot combines the interest distribution estimate with the neighbors' relative position to calculate its new position. The convergence to the optimal configuration is studied through formal methods and numerical simulations. Finally, the authors show how the system achieves better results letting the robots combine their local estimate of the interest distribution with the estimations of their neighbors, resulting in a sort of collective sensing.

7.3.2 *Chain formation*

In swarm robotics, a "chain" is a linear sequence of robots in communication range with their neighbors (see Figure 7.2). Chain formation is employed to connect two locations that cannot be simultaneously perceived by the individual robots due to their limited sensing capabilities. Once formed, the chains are exploited by other robots to efficiently navigate. In this way, the robots do not need any knowledge or map of the environment, nor any absolute positioning system (e.g., GPS), but they simply follow the chain to get to desired locations.

Chain formation takes inspiration from the foraging behavior of ants. Deneubourg et al. [9] showed that ants, when foraging, deposit trails of pheromone as a form of stigmergic communication to attract other individuals. As a result, the ant colony finds the shortest path between a nest and a food source. Similarly, robotic chains support the navigation between two areas. However, instead of laying pheromone trails, robots place themselves as trail markers. Each chain begins from a predefined home location, grows in random directions and possibly degenerates, until a target location is found and a path between home and target is established. The chain formation process is completely distributed and probabilistic. Robots explore the environment through random motion and join chains at random positions when they encounter one, therefore becoming trail markers.

With a given probability, the trail marker robots at the extremity of the chain leave and possibly re-join it at a different position. In this way, the chain can grow and disband following a self-organized process that leads to a continuous exploration of the environment until the target is discovered.

The first studies of chain formation methods in artificial distributed systems have been done in simulation [8, 10, 17]. In these works, the formation of a chain supports the robots in collecting objects in an unknown environment. Subsequently, this method has been implemented also on real robots [28, 42].

Other works focus on the exploitation of already formed chains to improve the efficiency of the robotic swarm in carrying out tasks that require navigation. For example, Nouyan et al. [29] implemented on real robots a distributed system able to solve a foraging task. In the investigated scenario, the goal of the robots is to retrieve an object (*prey*) and bring it to a specific area (*nest*). To support the exploration and the navigation in the unknown environment, the swarm allocates part of the robots to form a chain that extends from the nest in search of the prey. Once found, the remaining free robots exploit the chain to get to the prey and to transport it to the nest. Figure 7.2 shows a picture of the experiment in which a robotic chain connects the nest to the prey. Another example is the work of Campo et al. [5], where a swarm robotics system exploits already formed chains to select the shortest path to a target.

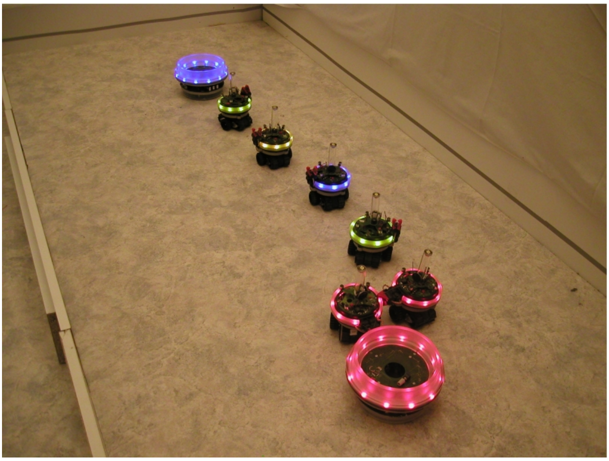

Fig. 7.2 A chain of robot connecting the nest to an object to be transported.

In the work of Hauert et al. [19], a swarm of Micro Air Vehicles (MAVs) self-organizes to establish and maintain a wireless communication network between users located on the ground and the base station. The vehicles rely only on local communication and compass, without absolute nor relative position information. The controller of the MAVs has been designed through artificial evolution. The resulting behavior is a chain formation process in which the MAVs, after take off, place themselves at the beginning of the chain to extend it. They keep their position by flying in the smallest possible circular trajectory. The continuous movement of the MAVs and the intrinsic noise of sensors and actuators cause temporary disconnections from the base station. This alternation of connection and disconnection phases provides the basis for a synchronized sweeping movement of the entire swarm, which allows to explore the environment and to connect users (with unknown location) to the base station. This work is part of the *The Swarming Micro Air Vehicle Network (SMAVNET) Project*[2], during which the controller has been brought on real MAV platforms.

Ducatelle et al. [11] study the problem of redeployment, that is how to correct the positioning of the sensors in order to increase the efficiency of the whole network. In particular, they focus on the scenario of assisted navigation where ground robots receive instructions of how to move in the environment (navigation instructions) by a swarm of ceiling robots which constitutes the overhead sensor network. The ground robots have to move back and forth between two predefined locations. The general idea is that the ceiling sensors adjust their positions moving to areas effectively navigable by ground robots which have movements constrained by obstacles on the ground. The new deployment position is determined by monitoring the traffic of the robots on the ground, and moving towards directions where they travel more often. Using this simple method, eventually, the network's topology converges to a chain that connects the two locations by the shortest path. This redeployment method helps when the initial configuration of the sensors poorly matches the placement of the obstacles in the environment, which can be due either to a poor initial deployment, or to a high complexity of the scenario.

7.3.3 *Communication assisted navigation*

Similarly to chain formation, the network resulting from communication assisted navigation aims to support the navigation between two locations. In chain formation, some robots of the swarm become part of the sensor

[2]http://lis.epfl.ch/smavs

network (*sensors*), while the others exploit the network to navigate in the environment (*followers*). Differently, in communication assisted navigation, the robots that act as sensors do not take static position and do not become static landmarks, but they are sensors and receivers at the same time. While the robots move in the environment and carry out their task, they locally communicate with the other robots in order to mutually get and give navigation instructions. The integration of these instructions allows the swarm to move efficiently in the environment.

Gutiérrez et al. [18] propose the *social odometry* algorithm, which produces a self-organized collective behavior that lets groups of robots navigate more efficiently in the environment. Social odometry works as follows. Once a robot has visited a target location, it keeps up to date an estimate of its position by exploiting odometry. In addition to this information, the robot stores a confidence level, which represents how precise its estimation is. Confidence decreases as the travelled distance increases, in order to take odometric errors into account. Social odometry guides the robot to its target by combining its location estimate with the information gathered from other robots, in particular with the neighbors' estimated target locations, their respective confidence levels and the neighbors' relative positions. When the robots are numerous enough, each one is always in communication range with some other neighbors. In this way, the global result at the group level is a dynamic network between the two locations. This network aids the robots to filter odometry errors, and to improve navigation. The authors test social odometry in groups of simulated robots (varying the size up to 30 robots), and show how this technique improves the efficiency of the navigation between two locations.

Sperati et al. [35] study, through artificial evolution, strategies of efficient exploration and navigation for a swarm of robots. The task to be accomplished requires the robots to explore an unknown environment, find two distant target locations, and efficiently navigate between them. The synthesized controller resulting from the evolutionary process lets the robots self-organize in a *dynamic chain*, where the robots form two lines and keep moving between the two areas in opposite directions. Forming dynamic chains allows each individual robot to effectively travel back and forth between the two areas and allows the swarm, as a whole, to preserve the information of the area locations. Figure 7.3 shows a graphical representation of the process.

Ducatelle et al. [12] propose the *swarm navigation* algorithm in which the robots of the swarm, as in the previous work, navigate back and forth between two targets. When the robots meets with each other, they ex-

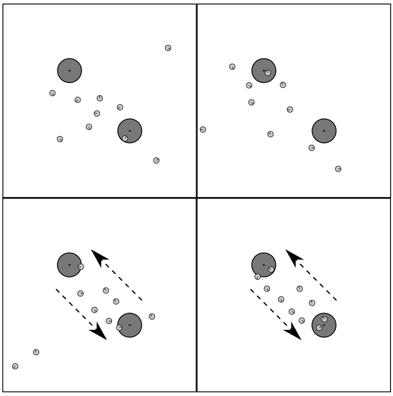

Fig. 7.3 The self-organized formation of a dynamic structure that connects two areas of interest, resulting from evolutionary optimization of the parameters of a simple neural network [35]. Robots initially start randomly distributed and progressively build a dynamic structure that connects the areas of interest.

change information of the target positions. If the robots are aiming to two different locations, they give each other navigation information about their respective targets, while if the robots aims to the same location they compare their estimate of the target position, select the newest of the two and start to move towards the same direction. This navigation strategy results in clusters of robots in communication with each other moving in opposite directions. When new information is received by any of the robots of a cluster, it spreads throughout the group, and the full cluster corrects its direction. If the number of robots is high enough, the clusters cover the entire distance between the two locations. At that point, the swarm organizes into a dynamic chain, where all the robots are in continuous movement towards one of the two locations. Keeping the robotic network in contact with the two locations lets the information of the locations position spread among all the robots of the network. In this way, the robots are continuously updated with perfect information about the direction where to move. This work has strong similarities with a previous work from Vaughan et al [40], however here the authors focus their attention only on the aspect of navigation, without any investigation on the emerging behavior of dynamic chains.

7.4 Discussions

The analysis of the current approaches in swarm robotics for exploration and navigation reveals many possible points of contact with the WSN domain. In some cases, the solutions proposed for robotic swarms have already been translated to mobile sensors, possibly with some modification, as is the case for the potential fields approach. In other cases, such as in the network-based navigation, routing paradigms and information sharing between neighboring robots are inspired from the WSN domain, and can inform novel developments with limited effort to prove convergence and stability properties, whenever that is required. Also for the chain formation approach a translation to mobile sensors is very straightforward. Despite the fact that chains do not provide a large coverage of an area, they can be exploited in mobile WSNs for tracking objects or for discovering and monitoring a limited number of points of interest. This approach is surely interesting, and similar studies are currently under development [13].

Differences between swarm robotics and WSN are mainly in the fact that swarm robotics solutions are based on fewer assumptions, which may lead to larger applicability to different domains and environmental conditions. On the other hand, in swarm robotics there is less emphasis on the demonstration of convergence properties, which are usually verified experimentally at least in a statistical sense, rather than formally demonstrated. Apart from that, it is evident that the solutions we reviewed for coverage, exploration and navigation are applicable to mobile sensors, above all when energy constraints are not tight, that is, when the hardware platform has sufficient autonomy, when batteries can be easily replaced or energy can be harvested from the environment. If energetic issues are constraining, then mobility is certainly expensive and must be limited, much as it should be limited the processing power of the single units. For this reason, among the different approaches for distributed multi-robot systems, swarm robotics is the optimal choice as it delivers simple controllers that exploit only limited sensing and processing abilities. Other approaches are much more demanding on the required processing power (e.g., multi-robot SLAM algorithms [21]), and may not be suitable for real word applications.

Finally, we believe that the best opportunities can be given by an hybridization of WSNs with robots [26]. In particular, with respect to swarm robotics the WSN may provide a useful infrastructure that can be exploited by the robots for minimal coordination and collaboration strategies. For instance, immobile sensor nodes can enhance the environment in which robotic swarms live, and can provide a mean to implement indirect coordination strategies based on stigmergy that would be otherwise difficult to implement. In this sense, WSN nodes can store structured information locally, which would facilitate the accomplishment of the task for the swarm robotic system. The advantages of such an hybridization between swarm robotics and WSNs are twofold. On the one hand, the robotic swarm can take care of deploying and redeploying tasks to optimize the network performance with respect to the events to be monitored, as well as to optimize the energy consumption across the network by replacing nodes with high consumption with less utilized ones (e.g., to mitigate the sink-hole problem), or to repair/replace malfunctioning nodes. On the other hand, the robotic swarm can exploit the WSN and the communication infrastructure to adaptively allocate tasks among robots, and to switch between exploration and exploitation in order to deliver the optimal number of robots to each task. Decision making processes can be therefore emergent form the interaction between mobile robots and immobile nodes, and can be developed following the properties of swarm robotics systems [5]. In summary, we believe that swarm robotics can greatly enhance the deployment and the redeployment of WSNs, which at the same time can offer to swarm robotics some environmental infrastructure that can be key to implement self-organized strategies for optimal group behavior.

7.5 Conclusions

In this chapter, we have addressed the problem of deployment and redeployment of sensing nodes in Wireless Sensor Networks, and we observed how mobility of sensors nodes can offer great advantages to enhance the coverage and the properties of the network. We have observed that mobility of sensor nodes naturally leads to robotic solutions, and in particular swarm robotics seems to be the best approach for large-scale distributed systems like mobile WSNs. Looking at WSN from a swarm robotics perspective reveals much more similarities than differences, and suggests a stronger integration of efforts in future research. Indeed, much advancement can be achieved in both domains by a concurrent development of solutions for swarm-like mobile WSNs. The research in this direction has just started, and much improvement is expected in the years to come, especially in the direction of delivering hybrid solutions for practical applications.

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