A Survey on Sensor Networks from a Multi-Agent perspective

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ABSTRACT

Sensor networks arise as one of the most promising technologies for the next decades. The recent emergence of small and inexpensive sensors based upon microelectromechanical system (MEMS) ease the development and proliferation of this kind of networks in a wide range of real-world applications. Multi-Agent systems (MAS) have been identified as one of the most promising technologies to contribute to this domain due to their suitability for modeling autonomous self-aware sensors in a flexible way. Firstly, this survey summarizes the actual challenges and research areas concerning sensor networks while identifying the most relevant MAS contributions. Secondly, we propose a taxonomy for sensor networks that classifies them depending on their features (and the research problems they pose). Finally, we identify some open, promising, future research directions for MAS research.

1. INTRODUCTION

Sensor networks have been identified as one of the most promising technologies for the future [4] [6] [16] due to: (1) the recent emergence of small and inexpensive sensors based upon microelectromechanical system (MEMS); (2) the set of advantages they offer in front of other monitoring technologies; and (3) the wide range of real-world applications that have been already identified for this technology.

As this new technology emerges and applies to real-world domains, it poses a variety of new challenges to researchers leading to some new active areas of interest concerning hardware and software.

In this survey we focus on the software challenges sensor networks pose from the perspective of multi-agent systems (MAS). Sensor networks have been identified as an application domain with high potential for MAS due to their suitability for modeling autonomous, self-aware sensors in a natural, flexible way [28] [16]. Sensor networks fall into the category of complex, distributed, interconnected and rapidly changing systems, identified in [10] as a hard and challenging domain for autonomic computing. Issues such as organizational structuring, coordination, collaboration and distributed, real-time resource allocation are critical for their success. In sensor networks, sensor agents may go beyond reacting to their local situation; they may collaboratively determine what to do and with whom while ensuring that certain collective, global properties are achieved. However, sensor networks may fairly vary from one to another depending on the features they exhibit. We realize that sensor networks with different features lead to different problems when considering its enactment an operation. Therefore, one of our contributions in this work is the definition of a taxonomy that classifies sensor networks in different families, each one leading to different problems of varying complexities when enabling them. We also identify the research topics with higher potential for sensor networks. Moreover, we summarize the most relevant contributions to these topics while identifying the sensor network's features in our taxonomy that each contribution focuses on. Finally, we realize a further analysis to identify open issues, and thus research opportunities that deserve further MAS attention.

The rest of this paper is structured as follows. In section 2 we introduce sensor networks analyzing their properties as a system and their suitability as an application domain for MAS. In section 3 we propose a taxonomy for sensor networks with the aim of classifing them in different families of problems while considering the most distinctive characteristics that influence the problem formulation. Next, in section 4 we identify the main research topics for sensor networks, describing the most salient contributions and results from MAS community. Finally, in section 5 we identify some research opportunities and, the most promising future research directions for MAS community.

2. SENSOR NETWORKS AND MAS

In this section we give a brief introduction to sensor networks. Moreover, and sensing devices distributed in a large area that collaborate to globally produce meaningful information from individual, raw, local data. They emerge as an alternative to other, already-existing monitoring technologies. Table 1 presents a comparison between sensor networks and other monitoring technologies. As we observe that the success of sensor networks lies in the advantatges they offer with respect to the alternative monitoring technologies. First, they are non-invasive and they can cover wide-range areas by using a large number of inexpensive and small sensors. Moreover, due to their distributed structure they are inherently fault-tolerant and robust to nodes failures and are suitable to monitor remote or hostile environments. Up to now, monitoring technologies have been concerned providing homogeneous collections of data and regularly sampled datasets. Nowadays, sensor networks can replace former technologies with heterogeneous data coming from different interest areas and pieces of information that vary substantially in content, resolution

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and accuracy.

Sensor Networks	Alternative technologies
Low-cost low-power simple sensors	**Expensive high-power consuming complex sensors**
Cover wide-range areas	**Cover small-size areas**
Monitor remote or hostile environments	**Monitor highly-controlled environments**
Fault-tolerance and robust to node failures	**Non-robust**
Non-invasive	**Invasive**
Irregular sampled datasets	Regularly sampled datasets
Intrinsic distributed structure	Intrinsic centralistic structure
Low-bandwith connectivity	High-bandwidth connectivity
Battery-powered	Electric-powered

Table 1: Differences between sensor network technologies and other monitoring technologies

Another motivating aspect of sensor networks is their range of applicability, leading so far to a large number of applications in very different domains such as habitat monitoring, biomedical applications, smart spaces or distributed robotics. The interested reader should refer to [30] [11] for surveys on sensor networks applications.

Finally, the research community has identified sensor networks as a very challenging domain because of the following distinguishing features:

Complexity. There is no easy way to manually design a sensor networt that acts properly in all possible environmental and network changes.

Scale. They are usually composed of thousands of nodes, making unfeasible approaches where the computational cost is exponential to the number of sensors. Hence, there is a need for scalable solutions that can consider a large number of sensors without limiting the effectiveness of the network.

Physical distribution. Sensors are distributedly deployed over some area. Hence, during their operation they have to deal with computation and information sources that are physically distributed.

Dynamics. Sensor networks are dynamic systems that by effect of its internal changes or by effects of external forces change over time. For example, sensors can appear/disappear over time in an unpredictable way. Hence, a sensor network' operation has to deal with and adapt to an underlying changing network.

Resource Availability. A key characteristic of sensor networks is that the demand for resources such as computation, power or bandwith, is always higher than supply. Thus, there is a need for resource-awareness at all operation levels of the network.

Interdependence. The network may need to coordinate different sensors to achieve high-level tasks that can not be achieved by the operation of a single sensor. Therefore, there are dependencies among sensors that make necessary to coordinate them during the sensor network operation.

Situatedness. Sensor networks are usually located in rapidly changing environments where the decision-making process of the sensor network has severe time restrictions. Thus, the sensor network may show anytime capabilities during its operation.

Notice that these characteristics make sensor networks a challenging domain for MAS. First, since sensor networks are inherently distributed, they can be modeled as MAS in a flexible way, and therefore take advantatge of algorithms and techniques proposed in the MAS literature. Concretely, sensor networks may be naturally modeled as MAS by regarding each sensor as an agent. MAS handle complexity and large scale systems offering modularity, decomposing the problem and assigning subproblems to different (sensor) agents. MAS is also used for modelling physical distribution and ad-hocness as a particular type of MAS. In resource-scattered environments, MAS provide efficiency by distributing computing, bandwith and power use among different agents. Moreover, MAS deal with: (1) rapidly changing environments that introduce severe time restrictions and with limited resources; and (2) with bounded-rational agents that try to maximize their expected reward but with limited resources. Finally, in complex and coupled problems, MAS research has dedicated years of effort to study how agents can interoperate and coordinate autonomously whereas achieving a desired global behavior through interactions.

3. A TAXONOMY FOR SENSOR NETWORKS

Although sharing a common definition, sensor networks may fairly vary from one to another depending on the features they exhibit. Moreover, notice that sensor networks' features deeply affect the problems and challenges posed when considering their enactment and operation. Here we try to identify such features defining a taxonomy to allow the classification of sensor networks. Our taxonomy classifies a sensor network depending on the characteristics of four elements: the sensing nodes, the network, the environment and the designer's goals.

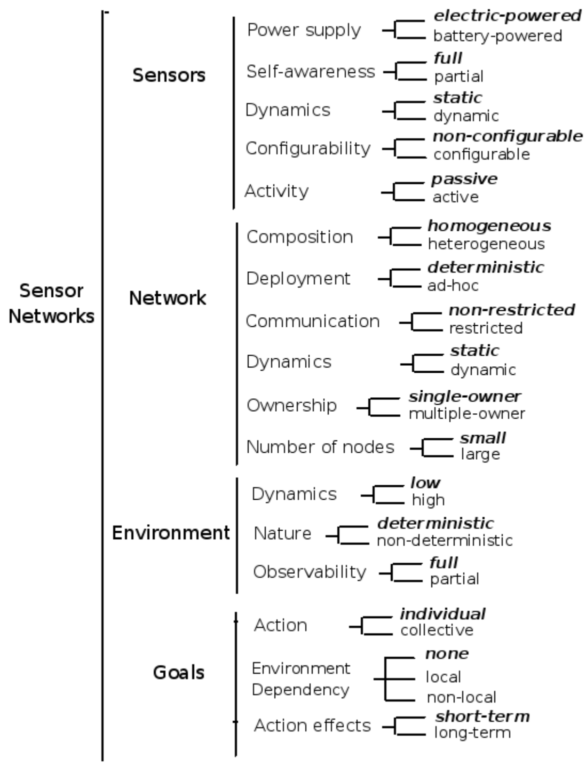

Figure 1: A taxonomy for sensor networks.

Fig. 1 shows our taxonomy where default features are boldfaced. In what follows we describe in detail the dimensions selected for each element.

3.1 Sensor nodes

Sensor nodes are the building blocks that compose sensor networks. These nodes, in addition to their sensing capabilities, also include a microprocessor and communication devices. Moreover, they may also include actuators that allow them to act over changes in the environment. From all sensor features in our taxonomy, we distinguish the following as the most salient ones:

Power supply. Nodes can be *battery-powered* when they have a finite power source; or *electric-powered* when their power source is infinite.

Self-awareness. A node can be *partially self-aware* in case some of its features are not directed accessible by the sensor network; or *fully self-aware* when the sensor network can access a complete representation of all its features. For instance, we consider nodes unaware of their own location or their battery levels as partially self-aware nodes.

Dynamics. A node can be *static* when sensors are assumed to remain unchanged except by the performance of actions executed by the same sensor network; or *dynamic* when external processes may affect it and modify it. For instance, we consider sensors that move or whose battery levels are recharged as a consequence of interactions in the environment as dynamic sensors. Dynamic sensors also include sensors that may disappear or be destroyed by the effect of the environment.

Configurability. Nodes can be *configurable*, when the sensor network can act over them setting their properties and setting different sensing, communication and processing capabilities; or *non-configurable* otherwise. Examples of configurable sensors are mobile sensors, sensors with different communication transmission powers, or sensors that can switch among different qualities of sensing.

Activity. Nodes can be *active* when they include actuators that they may use for modifying and introducing changes in the environment; or *passive* when their activity is restricted to perceive, process information and communicate. For instance, active sensor nodes can control illumination or heating sources or apply control forces over a material.

3.2 The network

The network in sensor networks is an entity composed of all deployed sensors and their communications links. We propose to characterize the network over five dimensions:

Composition. A network can be *homogeneous* when composed of sensors from the very same type (e.g. same level of processing, sensing or communication capabilities, etc.), or *heterogeneous* otherwise.

Deployment. A network can have either a *deterministic* deployment, when composed of the same sensors over time; or an *ad-hoc* deployment, when sensor positions are unknown before their deployment and they can not be set at design time. Deterministic deployment is common in friendly and accessible environments, whereas an ad-hoc deployment is generally considered in open or remote areas. For instance, forest monitoring sensor networks where sensors are deployed by throwing them from an helicopter are a good example of ad-hoc deployment.

Communication. Communication in a network can be *restricted* (due to low bandwith or costs or unreliability), or *non-restricted*. For instance, networks with RF transmission are a good example of restricted communication.

Dynamics. A network may be dynamic when composed of *dynamic* sensors or when communication links vary as a consequence of external processes; or *static* otherwise. For instance, a network whose sensor nodes appear/disappear in an unpredictable way is a good example of a dynamic network.

Ownership. A network may have a *single owner*, when all nodes are property of the same stakeholder or company, and *multiple owners* otherwise.

Number of nodes. A network may be *large* if composed of thousands of nodes, or *small* otherwise.

3.3 Environment

We define the environment as all external processes that are of interest to the sensor network. We propose to characterize the environment along three dimensions:

Dynamics. An environment can have *high* dynamics, when events and phenomena occur frequently and change the environment very rapidly; and *low* dynamics otherwise[1].

Nature. An environment can be *deterministic*, when any action has a single guaranteed effect and there is no uncertainty about the environment state that will result after performing an action; and *non-deterministic* otherwise.

Observability. An environment can be *fully-observable*, when sensors' observations can define the environment state without uncertainty; or *partially-observable* otherwise.

3.4 Goals

The last element of our taxonomy are the goals specified by a sensor network designer. The goals deeply affect the challenges that sensor network pose when enacting their operation. We use the following dimensions to classify a sensor network depending on the designer's goals:

Action. Goals can be achieved either through *individual* actions, when sensors' actions are considered separately, or through *collective* actions, when sensors' actions must be coordinated in order to achieve the goal. For instance, a sensor network with the goal of sampling an area such that each sensor adapts its sampling individually depending on the expected state can be considered as an example of goals with individual actions. Otherwise, multiple sensors sampling at the same time to obtain a useful measurement is an example of goals with collective actions.

Action effects. The actions' effects of the sensor network over the environment state (if nodes are active, can act over it); or the network state can be *short-term* or *long-term*. When actions have short-term effects, future network and environment states do not depen on actions executed in previous periods, only on the actions executed in the current period. If actions have short-term effects, the decision-making of the sensor network is easier because it only depends on the current network and environment states and it does not have to look ahead to consider future states. For instance, actions that have long-term effects on the underlying network are: actions that consume energy when limited (in battery-power sensors); actions that move sensors (mobile sensors); or actions that change sensor configurations when there is a delay or a cost to switch among them. On the other hand, examples of actions that have long term effects over the environment are: actions that move objects or action that modify certain environment conditions like the heating or the cooling of a room.

Environment Dependency. Goals may depend on the environment when the optimal actions vary with the environment dynamics. In case of environment dependency, the sensor network may need to estimate the current environment state (using sensor observations) in order to achieve its goals. For instance, a sensor network whose goal is to cover an area while minimizing energy consumption (by deactivat-

[1]Static environments are not considered in sensor networks because it makes no sense since there would be no phenomena to observe.

ing redundant sensors) is a good example of non-environment dependency. Notice that this goal does not depend on the environment, but on the sensor's joint actions. Otherwise, if the goals include tracking every detected object, then there exists environment dependency because the sensor network has to estimate the object position in order to track it. Moreover, environment dependency may be *local* when a sensor only needs its own observations to determine its local environment; or *non-local* if it also needs other observations.

4. RESEARCH TOPICS

The application of sensor networks to real-world domains poses a set of challenges to researchers leading to some new active areas of interest.

In what follows we describe what we consider as the main research topics for sensor networks: *localization*, *routing*, *information processing*, and *active sensing strategies*. Moreover, for each topic we review the main contributions from MAS research. Furthermore, in table 2, we summarize the features of the sensor network considered by each contribution, based on the taxonomy introduced in section 3, along with the employed approach and the research topic it contributes to. Notice that in table 2, the characterization of the sensor networks may specify fewer dimensions than the specified in the taxonomy. These non-specified dimensions stand for features that take the default values, the boldface features in the Fig. 1.

4.1 Localization

Each node in a sensor network can be aware of its own location as well as the identity and location of its neighbours. Typically, when sensors are deployed in an ad-hoc manner, the network topology has to be constructed in real time and updated periodically as sensors fail or new sensors are deployed. Moreover, due to this ad-hoc development nodes usually do not know their own position. Hence, localizing sensor nodes solving the problem of estimating its spatial coordinates is an important and popular area of research. However, contributions to this area typically stem from other communities different from MAS. Good introductions and reviews on these techniques can be found in [15] [19].

4.2 Routing

Routing algorithms in sensor networks have to be efficient in a network typically characterized as wireless (each node communicates using radio signals), ad-hoc (the set of nodes changes over time), and energy-constrained (nodes are battery-powered). Although in the literature different algorithms for ad-hoc wireless sensor networks have been proposed, they mainly focus on finding the shortest path without considering energy consumption or network lifetime. Therefore, an active area of research in sensor networks is the design of new, ad-hoc, wireless routing protocols that allow to route information in an energy-efficient way. Several recent surveys describe routing algorithms for wireless sensor networks [3][13]. However, most of these approaches are proposed from network research either by extending existing ad-hoc wireless routing algorithms or by proposing new ones. Therefore, we only review some significant MAS contributions hereafter. Probably the most salient contributions on this issue come from applying techniques from Computational Mechanism Design (CMD)[9]. CMD is a field that studies the development of agent interaction protocols to achieve a specific outcome (maximize a global function or achieve some global properties) taking into account the fact that agents are self-interested. This is usually done by designing mechanisms that give incentives to each agent to behave as the designer intends (usually a payment scheme that provides payments to the agents in exchange of their services). Along this line, Rogers et al. [24] develop a new energy-aware self-organized routing algorithm for sensor networks where sensors transmit only data to the sink. Their mechanism performs a greedy optimization because sensors take their routing decisions using only local information (the expected lifetimes and their distances to the sink and to their neighbours). In their mechanism, sensors use a communication protocol that allows sensors to find and select another sensor that is willing to act as a mediator and a payment scheme that ensures that sensors will only be acting as mediators in cases in which the overall performance of the sensor network is improved. Although this CMD schema is typically applied in sensor networks where sensors are owned by different stakeholders [23], they propose to apply it to the design of a single-owner sensor network due to the simplicity and well-studied properties of CMD. However, a comparison of the gain in terms of performance of these mechanisms in front of other well-known energy-efficient routing protocols is not provided.

In [21] Padhy et al. propose a new utility-based energy-aware self-organizing routing protocol combined with adaptive sampling (namely Utility-based Sensing and Communication protocol, USAC) that finds the cheapest cost route from an agent to the sink. The idea here is that it might be preferable for a sensor to transmit its data via a more energy-consuming route if the least energy-consuming route contains a sensor in a highly dynamic environment. Hence, the cost of a link from one agent to another is derived using the opportunity cost of the energy spent relaying the data instead of using this energy for its own sensing (sensors use a linear regression model to forecast the value of the future data).

4.3 Information processing

In sensor networks nodes usually need to exchange observations and data with other nodes to estimate their local environment state. Due to their communication and energy restriccions, a centralized state estimation, in which a single computational node receives all sensor data, is not possible. Hence there is a need for decentralized algorithms that allow sensors to estimate their state locally whereas minimizing the amount of bandwidth used. These algorithms must allow fusion occur locally at each node on the basis of local observations and the information communicated from neighbouring nodes considering that state estimates are often highly correlated between nodes. One approach along this line is the Decentralized Data Fusion (DDF) method [18] that provides a robust, modular and scalable solution to the problem of obtaining common and consistent state estimates across a sensor network by allowing sensors to communicate information rather than states. The use of information measures allows nodes to separate what is new information from prior knowledge and the fusion process is straightforward since fusion of information is additive (the order does not matter). Although DDF is limited to Gaussian distributions, an extension to this method [17], the BDDF algorithm, allows decentralization but without this limitation. Other works [5] [25] propose, as alternative to the DDF algorithm, the use of distributed particle filters (also known as Sequential Monte Carlo Methods) that can cope with highly dynamic environments and that can also handle non-Gaussian distributions. Particle filters are a set of particles or candidate state descriptions that are weighted

Ref	Sensor network features	Approach	Research Area
[24]	Sensors: battery-powered, partially self-aware, configurable; Network: ad-hoc, communication-restricted, dynamic, large; Goals: collective actions, long-term action effects;	Mechanism Design	Routing
[21]	Sensors: battery-powered, partially self-aware, configurable; Network: heterogeneous, ad-hoc, communication-restricted, large; Environment: highly-dynamic; Goals: collective actions, long-term action effects, local environment dependency;	Utility-based approach, regression model	Routing, individual active sensing
[18]	Network: dynamic, communication-restricted, large; Environment: partially-observable; Goals: non-local environment dependency	Decentralized Data Fusion method	Information Processing
[5] [25]	Network: dynamic,communication-restricted, large; Environment: highly dynamic, partially-observable; Goals: non-local environment dependency;	Distributed Particle Filters	Information Processing
[22]	Network: dynamic, communication-restricted, large; Environment: partially-observable; Goals: non-local environment dependency, collective actions;	Distributed spanning tree formation, distributed junction tree formation, asynchronous message passing	Information Processing, Collaborative Sensing Strategies
[23] [8]	Network: communication-restricted, multiple-owners; Goals: non-local environment dependency	Mechanism Design	Information processing
[14]	Sensors: battery-powered, dynamic, configurable; Network: communication-restricted; Goals: local environment dependency;	Utility-based , linear programming, regression model	Individual Active Sensing
[1]	Sensors: configurable; Network: large; Goals: collective actions;	Aproximate organization-based distributed algorithm	Coalition formation problem
[27]	Sensors: configurable; Network: ad-hoc, communication-restricted, large; Goals: collective actions;	Iterative negotiation process centralized to coalition managers	Coalition formation problem
[20]	Sensors: configurable; Goals: collective actions;	Combinatorial Auctions with central authority	Collaborative Sensing Strategies
[7]	Sensors: configurable; Goals: collective actions	Centralized search algorithms	Collaborative Sensing Strategies
[12]	Sensors: configurable; Network: large, communication-restricted; Environment: highly dynamic environment; Goals: collective actions, non-local environment dependency, long term action effects	Organizational-based, dynamic role assignment	Collaborative Sensing Strategies
[29]	Sensors: configurable; Goals: collective actions, non-local environment dependency;	Decentralized Data Fusion with Probability Collectives	Information processing, collaborative sensing strategy

Table 2: Contributions, sensor network features that consider, approach and research topic

depends on the observations and allow nodes to mantain a belief over state histories instead of just single states. For instance, in [25], Rosencrantz et al. use local particle filters to determine which measurements are worth sharing using a query-response system. In this approach, sensors keep a local particle filter and query one another for useful sensor measurements (a query is a small set of randomly selected particles). Sensors use query information to only transmit the most informative measures.

Another approach is taken in [22], where Paskin and Guestrin present a general architecture for distributed inference in sensor networks. They show that it can solve a wide range of inference problems, including probability inference problems. Their approach is based on distributing a typical centralized inference algorithm, the junction tree formation algorithm, considering the dynamic communication restriccions of the underlying network. They propose a novel architecture consisting of three distributed algorithms: spanning tree formation, junction tree formation and message passing. First, sensors organize themselves into a spanning tree so that adjacent nodes have high-quality wireless connections. Then, the spanning tree guides the formation of the junction tree in a way that computation and communication required by inference is minimized. Finally, the inference problem is exactly solved via asynchronous message passing on that junction tree.

Finally, in [23] [8], Rogers et al. attack the problem of sharing observations among nodes in a multiple-owner sensor network with communication restrictions using a CMD approach. Two problems arise in such scenario: first, communication resources may be distributed among nodes considering the value of the observation for each node and their communication links; and secondly, since sensors are owned by different stakeholders the mechanism must incentivate them to share information and to report a true valuation for the observations. In that context, they propose two allocation mechanisms, both incentive compatible [2]: one to deal with a network with broadcast communication (the problem is to decide who sends but not to whom) and another to deal with a peer-to-peer communication (the problem is to decide who sends and to whom). In both mechanisms the role of the auctioneer is centralized, and thus a central node computes the optimal allocation and payments. Moreover, they modify sensors' utility function, that sensors use to value any piece of information, to consider the communication link between agents and the probability of the information to be relevant to the agent.

4.4 Active Sensing Strategies

As considered in the taxonomy (see section 3), sensors can be configurable. That means that they can change their configurations to vary the content, resolution and accurancy of their observations. Therefore, the way a sensor network senses is not passive, and hence it must be provided with *active sensing*: the capacity of reconfiguring and coordinating its sensors in order to maximize the amount of information perceived over time.

We have classified contributions to active sensing strategies in two groups: individual, when each agent configures itself independently on the other agents, and collective, when agents have to coordinate in order to determine their joint configuration.

4.4.1 Individual

A type of active sensing well-studied in the literature is the active sampling where nodes use local information in order to reconfigure their sampling frequencies to only sense at the most informative moments instead of using a fixed frequency.

In [21], Padhy et al. develop, as part of their USAC pro-

[2]the dominant strategy is to truthfully reveal their private observations' values to the auctioneer

tocol, a novel mechanism for adaptive sampling that allows each sensor to adjust its sampling rate depending on the environment dynamics. Each sensor uses a regression model to forecast the future data as a function

of the last measurements and the optimal sampling rate is the one than keeps the confidence interval within a fixed limit. In this approach, an agent lowers its sensing frequency when he is capable of correctly predicting the next values, and increments its otherwise.

In [14], Kho et al. also develop a novel mechanism for adaptive sampling with solar-powered sensors that observe an environment that follows a pattern that is repeated over time (concretely they apply it to the real-time accurate flood forecasting problem). In such circumstances, each node has a new battery level each day and the available energy is distributed over the daily hours. Moreover, the phenomena of interest follow a daily pattern and the sampling rates of a specific hour can be used for estimating the sampling rates of the very same hour of the next day. In their approach, sensors adapt their sampling using a regression model to forecast the value of each sampling rate for each hour and solving a simple linear programming that maximizes the sum of these values constrained to the maximum amount of energy available for that day.

4.4.2 Collective

Collective active sensing strategies deal with sensor networks where sensors need to coordinate in order to collectively perform a higher-level sensing task. We identify two problems in this context: (1) the *Coalition formation problem*, namely when the sensor network has a set of tasks that need the collaboration of multiple nodes in order to be achieved. Hence, the problem is how to distribute sensor nodes into different coalitions, so that each coalition has enough resources to execute its corresponding task. Notice that this problem is not concerned with how nodes cooperate and organize within the coalition to execute the assigned task; and (2) the *Optimal control problem*, namely the problem of, given a set of tasks and a set of sensors nodes, determine the joint configurations that maximize the global task reward.

We divide MAS contributions to this issue based on whether they provide a solution to the coalition formation problem or to the optimal control problem.

Coalition Formation contributions. In [1], Abdallah et al. formulate the sensing strategy problem as a classic resource allocation problem where each agent controls some amount of resources and each task is worth some utility when the required resources are assigned. This formulation poses a coalition formation problem (how to assign to each task a coalition of agents that maximize the whole sensor network utility). To solve the coalition formation problem, they propose a novel distributed approximation algorithm guided by an underlying organization. Moreover, they propose the use of reinforcement learning techniques to allow agents to learn policies that speed up the search for future coalitions. The organization used is a hierarchy where the lowest levels represent resources controled by a single agent and the rest of levels are composed of managers that control and assign tasks to their direct subordinates. To achieve scalability, managers see an abstraction of the state of the organization that is under control. The price of this abstraction is a loss of information that leads to uncertainty in the manager state. When a manager receives a task, it asks in some order their children for contributions and assigs them subtasks (substasks are created by the manager by descomposing the original task) . If a manager can not successfully allocate a task, it forwards the task up in the hierarchy. To optimize the search, they use reinforcement learning to learn the optimal order in which each manager should ask children for each contribution. This approach makes some unfeasible assumptions for the sensor network domain: (1) the task utility function is defined with a fixed value if all necessary resources are assigned and null otherwise ; and (2) tasks can not share resources.

In [27], Sims et al. propose an iterative distributed negotiation process as a solution to the coalition formation problem that tries to achieve efficient allocations of sensors and adapt coalitions to a varying population of agents. Each coalition of agents corresponds to a sector whose agents work together to accomplish a fixed task, namely provide maximum coverage with the minimum number of agents. Managers are responsible for changing and negotiating over resources using an iterative negotiation process in order to maximize the global utility of the system. The proposed negotiation protocol is based on the Contract Net Protocol and unlike the original formulation it can deal with interdependent tasks (tasks that have positive utility for the same resources), whereas maximizing the global utility of the system. The negotiation process considers social marginal utilities as the sum of utilities of all agents involved in that negotiation. The protocol obtains either the optimal solution (when considering all the interdependences) or sub-optimal (when the chain of interdependences is cutted at some length). This approach also assumes that resources can not be shared among coalitions and that the negotiation process evaluates each resource separately without considering subadditive or superadditive relationships among resources.

Optimal control contributions. Abdallah et al. , in [20], propose to apply a market-based mechanism (combinatorial auctions) to the collaborative sensing strategy problem. They formulate a generalization of the classic resource allocation problem called the setting-based resource allocation problem. Unlike the classic problem, the setting-based one is applicable to domains where a resource can be configured to fulfill the needs of more than one task. Notice that this setting-based resource allocation problem allows not only to distribute resources among tasks but also to coordinate sensors in such tasks by giving a specific configuration for each sensor. In this approach, each task has a utility function that uses for submitting to a central node a set of bids over sensor configurations. Then the central node runs a combinatorial auction winner determination algorithm over the received bids and sends the winning configuration to sensors. To reduce the bidding combinatorial explosion, they allow the task utility function to evaluate partial configurations. At this aim, they use a Bayesian network to infer the world state and measurements probabilities and the value of sensor measurements. Notice that it is a centralized approach that does not consider the cost, neither in terms of time or energy, of continuously sensing all measurements to a central node and reconfigurations to sensors. Moreover, the techniques they propose, (using Bayesian inference to evaluate configurations for a task and combinatorial auctions to consider joint evaluations from all tasks) are computationally expensive and usually limited to small scenarios.

In [7], Dang et al. propose a solution to a problem equivalent to the setting-based resource allocation problem defined in [20] using a coalition model where each task defines a coalition. Then the problem is to find the set of sensor configurations that maximize the sum of all task evaluation functions considering also the cost of these configurations. With this aim they develop two centralized algorithms: a fast polynomial, approximate algorithm that uses a greedy technique and has a calculated bound to the optimum; and an optimal branch-and-bound algorithm.

In [12], Horling et al. propose an organizational-based approach to solve the collective sensing strategy problem when tracking one or more targets that move along arbitrary paths in an area [16]. The organization proposed considers fixed tasks (generate a scanning schedule for detecting new targets and keeping a directory service of sensors available) that does not depend on the environment and dynamic tasks that vary with the environment dynamics (the tracking of targets). To reduce communication burden, the global area is divided into static, non-overlapping, equal sectors, and global tasks are divided in subtasks defined over sectors and assigned to a fixed node, the sector manager. In response to new events (e.g. the detection of a new target) a sector manager creates a new task and assigns it to an agent (track manager). Notice that this assignment is dynamic and task responsability migrates among different agents. Track managers use their knowledge to determine from where and when should data be collected, ask sector managers for identifying the sensors needed to gather the information, send measurement requests to sensors it selects, and fuse received information into a continuous track. Sensors receive requests from track managers and sector managers. Although using this schema sensors may receive conflicting requests, authors are not concerned with this problem.

In [26] Ruairí and Keane propose a theory that deals with the coalition formation problem and the cooperation problem in systems, like sensor networks, where the set of tasks vary with the environment dynamics and where tasks exhibit an intrinsic locality. The Dynamic Regions Theory (DRT) is based on a dynamic partition of the network where each region executes an algorithm corresponding to a specific task. In this theory, agents not only consider in what region they are (in which task they contribute), they also coordinate with other agents in the same region in order to implement algorithms cooperatively. They give a particular example of how this theory can be applied in a bottom-up way to a wireless sensor network to allow the self-organization of the network. In this example they propose to use as a coordination mechanism an organitzation: each node executes a region identification process at regular intervals and a the regional organizational policy to implement role swapping both using local data. However, in this approach all the mechanisms are pre-set: rules that nodes use to identify its region and organizational policies to swap among roles. In addition to this, they do not consider that a node may be in and contribute to more than one region at each time. Finally, authors do not provide a discussion on the utility and advantatges of splitting nodes in regions with different algorithms instead of deciding each time the algorithm and the role.

In [22], Paskin and Guestrin also apply their architecture (see section 4.3 for an explanation of the application to information processing) for robust inference to the collective sensing strategy problem (what they call optimal control problem), by distributing a typical algorithm for centralized inference in a way that its computation and communication cost can be minimized.

In [29] Waldock and Nicholson show how Probability Collectives (PC), a powerful new framework for distributed optimisation, can be used for cooperative sensing in a decentralised sensor network. PC are used for sampling the joint space of sensor actions to discover an optimal collective sensing strategy. They use the DDF method (see section 4.3 for more details about this method) to share and fuse information with PC to sample the joint space of sensor actions to discover an optimal sensing strategy. Concretely, DDF and PC are coupled by an information-theoretic utility function: DDF operations create the utility function and PC determine the set of actions to take. The authors apply these techniques to the sensor-to-target assigment problems where the problem is to assign sensors to targets in order to maximize some measure of the system-wide performance (the quality of target state estimates). One important limitation to this approach is that if the utility of agents' actions vary when there are changes either in the environment or in the network, the already learnt probability distribution becomes useless and it needs to be learnt from scratch.

5. CONCLUSIONS

Despite the many and significant contributions to the different research topics, more research effort is required to allow the application of sensor networks to real-world problems. In what follows we analyse the most promising lines of research for MAS that pose open, challenging issues.

As to routing, research on energy-efficient, ad-hoc routing problems is still an open issue. Concretely, further work is necessary to develop new protocols that address larger changes in topology and higher scalability.

As to information processing, existing works focus on distributing the existing centralized inference and fusion algorithms to minimize the communication through the network. However, an important and still open issue is how to extend these algorithms to adapt and exploit the specific network topology and dynamics. Hence, how to distribute the processing load and the communication flow among nodes considering their energy and their communication restrictions are particularly interesting.

Research on active sensing strategies, concretely on collective sensing strategies, may become the most active MAS research topic. As to collective sensing strategies, some works ([20] [7] [1] [27]) have reformulated the problems posed by sensor networks as a more general and well-know problems, such as the classical resource allocation, the task allocation problem, or the coalition formation problem. However, few extend these more general formulations in order to exploit and adapt to the particularities of the sensor network domain. Therefore, an open issue is to adapt these contributions to exploit aspects like locality (interactions among closer physical neighbours or the definition of tasks over a region) or the sharing of resources among tasks (sensors can contribute to more than one task with their actions). In that context, exploiting the fact that coalitions are defined over regions to reduce the complexity of the coalition formation algorithms looks promising. Another focus of attention of collective sensing strategies lies on the study of the reorganization and adaptiveness of sensor networks to changes in the underlying network and environment. One interesting approach to deal with these changing conditions comes from works like [12] and [26] which, in the context of computational organizations, implement dynamic role assignment to allow agents to switch among roles in response to network and environment dynamics. However, their policies for switching are determined and they have been only applied to particular applications.

Another open issue in sensor networks, applicable to all research topics, is the introduction of learning. Except [1], the works included in this survey assume that the system has already prior knowledge about the utility of its actions and about how to infer and predict the environment state, excluding the need for using learning to improve the system performance. Moreover, the introduction of learning techniques in sensor networks may need the use of transfer learning mechanisms, namely mechanisms that allow to transmit what agents have learned so far in a former learning context to some new, similar context. Otherwise the changes in the network structure, due to its dynamics or the self-organization process itself, would require agents to restart their learning processes from scratch. The literature tackling this problem is scattered and maybe the most significant work is [2], where Abdallah et al. propose a mechanism to transfer knowledge by using heuristics in multi-agent reinforcement learning.

Finally, except [23] and [8], few works consider that a sensor network may have multiple owners. Moreover, although these works have shown that Computational Mechanism Design is useful for modelling these scenarios, the allocation and payment rules are usually centralized. Therefore, building decentralized mechanisms where the auctioneer role is distributed among the participating agents remains an open issue.

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