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Review

Towards the Robotic "Avatar": An Extensive Survey of the Cooperation between and within Networked Mobile Sensors

Sebahattin Topal *, İsmet Erkmen and Aydan M. Erkmen

Mechatronic Laboratory, Department of Electrical and Electronics Engineering, Middle East Technical University, 06531 Ankara, Turkey; E-Mails: erkmen@metu.edu.tr (İ.E.); aydan@metu.edu.tr (A.M.E.)

* Author to whom correspondence should be addressed; E-Mail: stopal@metu.edu.tr; Tel.: +90-312-210-45-90.

Abstract: Cooperation between networked mobile sensors, wearable and sycophant sensor networks with parasitically sticking agents, and also having human beings involved in the loop is the "Avatarization" within the robotic research community, where all networks are connected and where you can connect/disconnect at any time to acquire data from a vast unstructured world. This paper extensively surveys the networked robotic foundations of this robotic biological "Avatar" that awaits us in the future. Cooperation between networked mobile sensors as well as cooperation of nodes within a network are becoming more robust, fault tolerant and enable adaptation of the networks to changing environment conditions. In this paper, we survey and comparatively discuss the current state of networked robotics via their critical application areas and their design characteristics. We conclude by discussing future challenges.

Keywords: networked mobile robot systems; hybrid sensor networks; survey

1. Introduction

Sensor networks are relatively young and a challenging area of research. Their primary aim is to collect and communicate environmental data for cooperatively monitoring and controlling their physical surroundings. Figure 1 shows how research on mobile sensor networking has proliferated in the last decade especially due to advances in computation, communication, sensing and actuation technologies. Mobile sensor networks, which are composed of navigating units such as heterogeneous

robots and unmanned air or ground vehicles, transmit data through wireless communication networking. These units can typically communicate with each other via implicit or explicit communication techniques. Many applications have emerged in a variety of fields such as wide area surveillance, reconnaissance, search and rescue in disaster environments, and planetary exploration, which are overviewed in Section 2.

Figure 1. The number of publications on mobile sensor networking research in the Web of Science from 1995 to 2009.

Web of Science Analyze Results from 1995 to 2009

■ Mobile Sensor Network or Multi robot
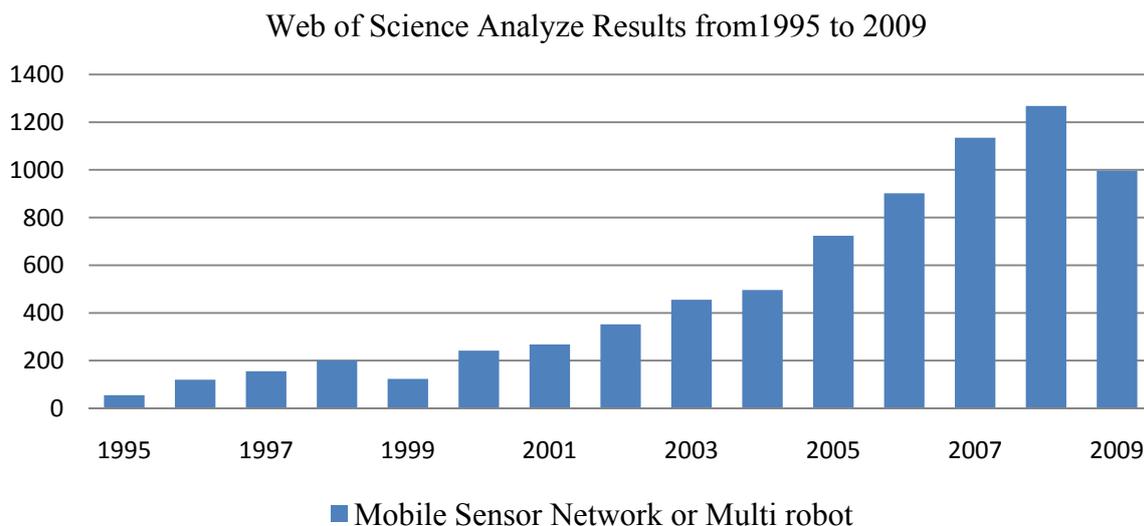
The focus of this survey is mainly on networked mobile sensors, which have various advantages in comparison with static ones. The most prominent advantages reside in the cooperation between different robot networks as well as the cooperation of robots within a single network. Sensing, acting, communication, computation and locomotion capabilities of networked mobile sensor systems result in improved efficiency in the execution of hard tasks especially with the help of their mobility capability [1]. As a counter example, monitoring and surveying an uncertain environment using static sensor networks is done through the acquisition and fusion of data by static nodes to the extent of their spread over the area [2,3]. The major problem faced for reconnaissance tasks is inefficiency in area coverage [4–6], since deployment control during the spreading of static nodes is weak or non-existent. Static sensor networks are spread over an area using airplane, land vehicle, human or animal, and so sensor coverage is heterogeneous. This problem has been overcome by using mobile sensor networks, which are composed of simple mobile robot units deployed over the area for controlled coverage that can be further optimized during network deployment and be still modified under task changes. Mobile sensor networking requires a large number of sensor nodes to be deployed within an environment for efficient surveillance, monitoring, data harvesting and search tasks [7–11]; efficient coordination is critical for accomplishing a given task with a large number of networked robot units. We undertake a survey of the evolution of the abilities of mobile sensor networks that have been achieved over the years as reflected in the literature. This will be the focus in Section 3, namely coordination control, fault tolerance, seamless communication, holonic reconfigurability and scalability.

Despite those advantages, there are some shortcomings of mobile sensor networks. They face the problem of deployment and adaptive coverage, which are energy devouring processes, by each mobile

unit of the sensor networks [12], and mobile sensors are more expensive than static ones. A considerable amount of energy must be spent for the locomotion task, and so the lifetime of the network is very limited, *i.e.,* a given task has to be accomplished within a very constrained time frame. Changing a mobile wireless sensor network system into a hybrid union of static and mobile sensor subnetworks, cooperating for efficient deployment and coverage in an energy saving mode, makes the usage of hybrid sensor networks a more tempting architecture in order to improve the efficiency of the system. The main idea in hybrid network systems is that mobile nodes collaborate with the stationary ones. Existing works in the literature about hybrid sensor networks are overviewed in Section 4. However, the joining of static sensor subnetworks with mobile ones shifts the load of correcting the heterogeneity of the coverage that static subnetworks inherently exhibit, to the nodes of the mobile subnetwork. This compensation increases the energy need, thus decreasing the efficiency. A recently emerged novel concept of Sycophant Wireless Sensor Networks (SWS) was developed as static sensor networks that are equipped with limited mobility ability and these are overviewed in Section 4. A SWS network is a clandestine traveler that passively uses the mobility of carrying agents to collect, process, and communicate data harvested during the agent's navigation. However, it cannot in any circumstance guide or influence the motion of the carrying agents.

Nowadays, mobile sensor networks are increasingly gaining new abilities with emerging new hardware, software and biologically inspired approaches. In turn, many future scientific challenges exist in the networked mobile sensor research area such as biologically inspired self-organizing robot networks, completely decentralized controller networks, scalability, heterogeneous robot networks which can cooperate with humans and intelligent environments. In this paper, we provide a comparative survey of existing approaches based on the span of their focus and their advantages or disadvantages brought to this field of interest and we dwell on potential future challenges of networked mobile sensors in Section 5.

2. Application of Networked Mobile Sensors

This section attempts not only to go over the abilities attributed over the years to mobile networked robot systems, such as simultaneously localization, mapping, exploration and surveillance, but also to overview critical applications of networked robots, including search and rescue operations in hazardous areas hostile to humans and military applications with strategically tasks.

2.1. Simultaneous Localization, Mapping and Exploration

Autonomous environment mapping and exploration are important missions for real world applications where global position data (GPS) is not available, such as semi-collapsed buildings due to an earthquake. In simultaneous localization, mapping (SLAM) and exploration missions, robots try to answer the questions of *"What does the world look like?"*, *"Where am I?"* and *"Where do I have to go next?"* by using noisy range sensor measurements and noisy travelled distance measurements coming from encoders, obtained from unknown environments. This is a chicken–and–egg like problem, which makes the problem difficult to solve; each robot needs an accurate environment map to localize itself accurately in the work space, but robots also require their exact position to generate an accurate environment model.

Smith *et al.* [13] proposed an Extended Kalman Filter (EKF) method for estimating the posterior distribution over robot position along with the positions of landmarks in the work environment. It is an initial work that established the fact that there is a statistical relationship between each landmark location and observations. Assumptions made by a Kalman Filter (KF) are that noise in the system is Gaussian distributed with zero mean and the process is linear. These are quite error prone considerations for complex real world applications. Linearity constraint is handled by the extended version of KF, namely the Extended Kalman Filter (EKF), which is used considerably for the solution of SLAM problems in the literature [14–16]. Although EKF based SLAM methods are historically the earliest used approaches that work well for environments in which there are limited number of features, computational complexity increases with an increasing amount of features. Hence, computation burden and Gaussian assumption in the probability density function are the shortcomings of the EKF based SLAM algorithms [17,18].

An alternative particle filter (PF) based method for SLAM problem was introduced by Montemerlo *et al.* [17,19]. Particle filter based approaches are approximations of Bayesian filters such that probability distributions are approximately quantized by a finite set of particles [20]. Thus, arbitrary multimodal distributions can be approximated by using a sufficient amount of particles. The most advantageous characteristics of PF for SLAM problems are the abilities of handling nonlinearities and non-Gaussian noise. However computational complexity increases with the number of particles, which makes the real-time implementation of PF difficult in complex and hard real world applications. Hence, the FastSLAM method, which is a modified version of PF, has been proposed to handle the computational burden in classical particle filter methods so as to successfully be implemented on real robots [17]. This proposed method utilizes a Rao-Blackwellized representation which integrates PF and KF representations. FastSLAM uses PF to estimate the robot navigation path and each particle runs EKF to estimate map feature locations. Since each particle generates an individual map representation of the work environment, the FastSLAM algorithm suffers from memory constraints. To improve the memory efficiency of the method, genetic algorithm based improved Rao-Blackwellized approaches are proposed by Feng *et al.* [21].

In order to increase the accuracy and efficiency of SLAM algorithms, putting emphasis to better map building of the unknown work environments, networked robot teams have been equipped with map merging capabilities [22]. Each robot extracts a partial map of a different portion of the large environment and those partial maps are merged into a single joint map to speed up the mapping process. SLAM problem becomes complex in the phase of data fusion, integrating the different partial maps into a global one based on the cooperation of robot units. Burgard *et al.* [23] addressed the multi-robot mapping problem under the constraint that each robot has the initial position and orientation information of all group members, and all robots share their motion and range measurements with other robots to generate a single joint environment map. This assumption makes the proposed solution unrealistic in real world applications, especially in the case of a limited communication range between robots and because initial robot localizations and orientations are not exactly known. Generally, the initial position of the robots will not be known as *a priori* information and this initial uncertainty generates a crucial question as to how to merge partial maps obtained by different robot units. In [24], Carpin *et al.* presented such a map merging case for multi-robot network by rotating and translating the partial maps of the environment developed by each robot unit until similar regions overlapped.

Although the presented methodology can merge partial maps successfully into a joint global map, it is not suitable for real-time applications because of time inefficiency. If spectral information of the partial maps is used as in [25], joining partial maps of large environments can be more accurate and fast. There, map merging is evaluated in two separate steps: the first uses rotation transformation calculations, and then translations in the x and y direction are extracted. Orientation estimation is done using Hough spectrum and translation is computed via basically the pixel intensity value projections on the x and y axes of the environment maps. In order to successfully fuse partial maps, it is necessary that the individual robot maps being merged have a significant degree of overlapping region and the work area must be well structured, such as in the case of indoor environments. Finally, each generated map must be in the same scale. These are the shortcomings of existing works concerning merging partial environments maps.

The generation of 3D maps by robots about their work environment is a crucial mission for high level and complex task executions such as carrying a buried victim within the debris or exploring mines where safety of navigation for the robot can only be achieved by extracting the 3D model of the work area. In [26], Thrun presented an approach to construct 3D occupancy grid models of the outdoor terrain by using 2D laser range finders that are mounted on a remotely controlled helicopter to learn the 3D representation of the outdoor environments. Although, flying robots increase the mobility in complex and natural terrains, surfaces are sensed only once, which is the limitation of their work, since establishing connections between previously mapped areas is a critical issue for map fusion and those correspondences are generated by revisiting mapped areas. Recently, some works have been proposed to use vision systems for SLAM, where image based data fusion is found to be more practical and natural due to fact that vision systems are cheaper than range scanners and more quality information can be obtained using cameras. Visual SLAM methods [27–29] can be classified in terms of stereo and monocular approaches to extract 3D visual landmarks from the environment. Feature initialization is an important problem in monocular systems. However, features cannot be initialized exactly into the existing map using only one measurement because of their unknown depth values, thus Davison *et al.* [30] proposed a delayed initializing methodology using a monocular approach in which the algorithm waits until the camera position has enough parallax to determine the feature's position. The proposed algorithm needs a particular depth interval in the features, which cannot be met in the real world, where feature depths can be very near. This renders the algorithm not efficiently applicable in real world applications. They also use corner-like features due to the fact that data association is relatively easy for corners. However, in the environments where limited numbers of corners exists such as corridors or areas with a high number of smooth surfaces, this monocular SLAM system can crash. Because of the aforementioned disadvantages of monocular SLAM, stereo camera systems have been used to provide more robust 3D maps [31]. Gil *et al.* performed a visual SLAM using a Rao-Blackwellized PF with autonomous networked robot teams. In their system, each robot is equipped with a stereo camera that provides relative measurements between landmarks, which are then used for data association. This paper is the first work regarding the building of a common 3D map of the environment by using visual measurements provided by multi-robot team. However, this method is only suitable for robot networks with a small number of units, because the computation burden grows significantly with the amount of robots involved. The proposed algorithm is also not suitable for outdoor operations since robot navigation is restricted to 2D motion: when robot motion capability is

extended from planar to 3D, the size of the state vector increases leading to an increase of the computational burden exceeding any acceptable limit for online applications.

Another important task for networked robots in the mission space is exploration. Unfortunately, numerous researches are using single robot systems to simultaneously explore and create maps in an unknown environment such as search and rescue areas [32–35]. The most important disadvantage of single robot usage is that it takes much more time than networked robot systems. Time efficiency in the distributed system comes from task partitioning and coordination between robot units. Coordinated multi-robot systems win over single robot approaches, dealing with limited communication range, map merging into a better global map of the workspace and better time constraints [36,37]. To date, the major portion of coordinated exploration works has focused upon coverage of an entire area in minimum time [38,39]. These techniques are based on the selection of the best next observation point for each robot in order to reduce the uncertainty of the environment map. Frontier cells, which are the cells on the borders between explored and unknown space, are taken as possible next observation points. Existing methodologies only dwell on SLAM solutions that minimize only the cost of reaching the target observation point and expected information gain. Entropy based methodologies are geared towards optimal data acquisition for localization but with very limited exploration.

No guidance to the robots about the purpose of the exploration mission therefore exists. Any additional information about the aim of the exploration, such as prior information about the work environment, can be a valuable guidance for the exploration. Preferred regions with the highest likelihood for finding victims can give a priority to the exploration, called prioritized exploration. We have developed an active exploration methodology based on percolation guidance, where a percolator estimates the existence of connected voids in the upcoming yet unexplored region ahead of the robot, so as to increase the efficiency of the reconnaissance operation by the superior ability of the percolator guidance for speedy coverage of the area [40–42]. However, proposed prioritized exploration approaches coverage does not become solely a primary issue. There, space coverage and time optimization are mainly aimed through guidance, based on either prior knowledge, or on extra information reflecting the characteristics of the environments that lead to the estimation of connected voids by a percolator for the areas to be explored. These techniques have high map coverage accuracy, while being adversely affected by errors in robot localization that would be minimized if exploitation was done. On the other hand, entropy based SLAM methods put exploitation as their primary goal, and exhibit poor coverage while achieving high localization accuracy. Percolation enhanced entropy based SLAM harnesses both exploration and exploitation by switching between the two under a switching controller, depending upon whether position or map accuracy is needed during FastSLAM [42].

2.2. Surveillance

In the past decade, terrorist attacks have raised some new research issues like that of surveillance using networked autonomous vehicles. Surveillance is the mission of observing the movements of targets navigating in a risky urban environment, such that robots can be considered to assume the role of security guards. Static sensor network approaches have been commonly used for such missions, but they were found to fail in complex applications such as surveying dynamic and open areas. The reasons for failure are generally about the limited sensing range of the sensing devices, the very large

work space to be covered during observations and the non-existence of prior knowledge about how to deploy the sensors [43,44]. Nowadays, networked mobile sensor systems are widely used for surveillance missions because of the decreasing cost of the autonomous platform development and the increasing abilities in navigation, sensing and computation [45]. Surveillance missions generally include target detection and tracking, under the coordination of mobile robots of the network.

Especially in video based surveillance methods, target detection is a considerably problematic issue because of natural, uncontrolled environmental conditions such as scene variety and illumination. Li *et al.* [46] used a hybrid Gaussian mixture model with temporal frame difference for detecting moving objects in environments where illumination can change suddenly. Their approaches also handle wrong labeling, which occurs when targets come at very close proximity to each other using a "record" strategy. Another research area dealing with surveillance is the physical tracking of targets, which involves continuously adjusting velocities of robots in order to keep track of the target within the viewing distance of the tracker robot. Sarwal *et al.* [47] handled the tracking of a target using multi robot systems, using a reference list that a robot maintains, so that it does not track an encountered target if that target is being tracked by another team member.

Parker [48] developed a distributed coordination control strategy that observes the movements of targets in the task area for being processed by networked robot systems. This work is the first research regarding multi-robot surveillance in complex and geometrical environments. Mobility and cooperation abilities provide successful task accomplishment despite a robot's limited sensing range. Robots can follow targets using local force vector based methodology and these vectors also handle the consistency problem of observing a target by multiple robots using a back force. The given algorithm minimizes the total time in which targets can escape from the pursuit by some robot team member in the area of interest, which is an important real-time need in unknown and dynamic environments. The limitation of the method relates to the work environment: the algorithm works only in areas without obstacles or where only a few simple convex obstacles exist, since the algorithm is very sensitive to detection errors. A distributed coordination control algorithm for surveillance missions by multiple robots was presented by Kolling and Carpin, whose method is an extension of the work by Parker [49]. Their algorithm, named Behavioral Cooperative Multi-robot Observation of Multiple Moving Targets (B-CMOMMT), is based on Explore and Help behaviors that keep the targets under observation by utilizing information supplied by sensors. However, this method also suffers from constraints of the operation environment. Kolling and Carpin [50] later presented a graph theoretic solution to the environmental problem encountered in their previously referred work, by modeling the complex work area as a graph. In their model, the environment is partitioned into nodes and their Graph-Clear module determines the minimum number of robots needed to mark all targets. Consequently, robots coordinate their actions to achieve this goal of marking targets in the graph modeled complex environment.

Surveillance is not only done by groups of ground vehicles, but also is done by air vehicles. The use of networked Unmanned Air Vehicles, in short UAV, has potential benefits since they can cover very large and remote areas and they can identify very small targets via technologically-advanced cameras. Heterogeneous networked unmanned ground vehicles (UGVs) and unmanned aerial vehicles (UAVs) are used for searching targets in predetermined large battlefield operation areas as introduced by Grocholsky *et al.* [51]. Aerial and ground vehicles have complementary capabilities and characteristics. Networked air vehicle teams can cover large areas much quicker than ground vehicles.

However, air vehicles cannot exactly localize targets because of altitude and limitations in the resolution of sensing devices. At that point, ground vehicles help them by using their high resolution sensors for localization process.

Feasible path planning for each vehicle in the network and strategy generation for obstacle avoidance are other research issues within surveillance operations which critically affect the efficiency of time and energy of the system performance. Multi-robot path planning, for example, generally causes multiple area coverage creating redundancy of exploration, which can turn into advantages for correcting errors in mapping. However, time and energy have to be consumed for building such accuracy in mapping by error correction based on redundancy. If time and energy become primary issues, multiple area coverage should be prevented when it is detected by the algorithm. Decentralization is the main cause for this need of compensation. Authors have tried to provide centralization to some local problems of networked mobile robotics. Cai and Peng [52] used a novel adaptive genetic algorithm based cooperative path planning algorithm for networked robot systems. Although the proposed algorithm is robust for convergence, it is a centralized method and suffers from the limitations of centralization such as computation burden and single point failure. On the contrary, Berg and Overmars [53] gave a decentralized prioritized motion planning method for various types of robot platforms such as flying and wheeled robots or manipulators. A priority is assigned to each robot, then a robot is selected according to the highest priority and a feasible path is planned for that selected robot, considering also dynamic obstacles inside the work environment.

2.3. Search and Rescue Operations

One of the main application areas for mobile robot teams is search and rescue operations in disaster environments. Different kinds of catastrophe occur in nature such as earthquakes, landslides and fires. Usage of networked robot systems is of great importance under these disaster situations [54]. Robots consistently help humans in dangerous and complex tasks, providing information about areas that cannot be directly reached by the humans, especially in disaster areas, which are typically highly unstructured and uncertain. Search and rescue teams of living humans have the main disadvantage of tiredness from continuous and tedious long hours of works, so robotic aids are increasingly being considered in search and rescue tasks [40]. Networked mobile robots show promise to be a highly versatile system for disaster reconnaissance, building the inventory of the disaster while searching for survivors.

The most important search and rescue task for networked robot teams in a disaster environment is the localization of victims within the disaster rubble, so as to provide information about the condition of detected possible survivors in the disaster areas not easily reachable by humans. Heterogeneous networked robot teams were constructed by Sato *et al.* [55] to cooperatively control each other to find survivors. The heterogeneous rescue teams are composed of three kinds of robots, each of them equipped with different abilities: MA-I is a track type inspired from tanks and is remotely controlled by an operator over a radio signal, IGA is a track type with flippers, which gives the ability of navigation in rough terrain, and KOHGA is a snake-like robot. Differently structured robots are used to improve mobility with the help of the robots' flippers, snake-like motion and the capability of physical support. For example, when a robot is trapped into the rough terrain by obstacles and cannot recover its

mobility, other robot team members can give physical support to the trapped robot to escape from its failed position. This improved robustness in mobility has promising capabilities for safe navigation in challenging unstructured environments.

Task execution, like for exploration, mapping and navigation, can be very difficult due to the structural characteristics of the disaster environments. Networked robot systems can handle these difficulties, not only by using information sharing but also by reshaping their morphology and passing some components to each other; this is called force cooperation in the literature. These networked robots are called reconfigurable robots and can execute complex tasks that the information-only coordinated robot team with fixed structure cannot execute [56,57]. Reconfiguration capability provides flexibility to the robot team when accomplishing difficult tasks in urban search and rescue missions such as transportation of victims in the catastrophe area and helping other failed robots in the team to recover, or coverage of the failed robots in accomplishing the rest of the given mission [56]. Wang *et al.* [57] investigated force cooperation between networked robots to enhance the mobility of the team. The proposed networked robot system can dock and adjust each team member's position and orientation according to other robots' states to easily execute a given task using force cooperation. Hard environmental conditions such as hills and being trapped in a trench are handled by using this docking skill.

Another problem for search and rescue teams is the mechanical development of robot platforms, since some of the robots need to be small and have high mobility while others need be powerful and robust. Simple small devices are used for debris exploration making use of their high maneuvering capabilities and powerful robotic devices are used for treating heavy debris, opening passages and carrying victims out of collapsed buildings. There are various types of rescue robots, being either autonomous or human operated [58–60]. The Helios VII arm-equipped tracked vehicle is a simple yet robust robot developed by Guarnieri *et al.* [58] to explore debris. It has a mounted arm that assists the motion of the robot and can also be used for manipulation. The robot navigates through very harsh environments with the help of its tracks. Turned upside down, it is able to flip over using the mounted arm. In [59], Tanaka *et al.* reported a high power rescue robot to move big obstacles and to carry a victim out of debris as soon as possible using a high-pressure hydraulic actuator. After the localization of victims by a small robot with a high capability for maneuver, powerful robots carry the survivor out of the debris or helps human beings in the transportation of heavy obstacles.

Existing networked mobile robot systems are not yet fully operable during real and hard catastrophe management activities due to limitations of the sensing, navigation and decision making capabilities of mobile sensors and robots.

2.4. Military Applications

National military forces always try to use technological developments to reduce the risk of soldier death and injury by producing highly technological weapons and vehicles. These reasons make the military field a very reasonable application area for robotic systems. Walking through minefields, surveying borders, executing logistic operations and destroying dangerous materials are some examples of the usage of networked mobile systems in the military applications [61–63].

Nowadays, autonomous Multi-Unmanned Air Vehicles (MUAVs) have great importance in the field of military for reconnaissance applications [61]. UAVs flying without a human crew are used to report militants' actions before any attack. Because of limited sensing and communication range in highly strategic and secret missions, vast operation areas, and power issues, multi UAV systems have been preferred over networked ground autonomous vehicles. UAV systems have become very popular in military missions, since they can collect information from different locations and fuse them for decisions about the next action that each member of the group has to take and send collected information to an operation center. They are also fault tolerant, flexible in surveillance tasks and highly versatile, spanning a large variety of application areas. Large coverage areas can be monitored due to cooperation of swift units of the UAV network and coordination in the exchange of sensory information acquired individually from the work environment.

Maza *et al.* [63] developed a team control strategy for a distributed UAV network not only for observation of critical areas but also for deployment of small sensor nodes in the mission environment. By deploying new sensors in areas deprived of continuous communication, the UAV network repairs the connectivity of the existing network. The given architecture is also designed for cooperatively carrying heavy loads by three UAVs. It is the first attempt to carry a military load with three UAVs. Networked micro-robot teams that have complex sensing abilities are a challenging research topic for military operations. They can effectively percolate into hazardous environments and send information about the state of the enemy. Many limitations exist, e.g., robot units must be small enough to reach small areas and be inexpensive. Minimum power consumption is another very critical design issue. If these critical issues are solved, micro robot teams will perform a very critical duty in the military applications and reduce the danger of death to humans in the wars.

Santana *et al.* [62] proposed a heterogeneous multi-robot system for humanitarian demining, including mine and minefield detection. Their system includes human operators, UAVs, legged and wheeled robots, where complexity is reduced through cooperation and coordination of the different units. UAVs are used to detect mines. Legged robots have the capability to walk in rough and unstructured terrains and wheeled robots have high navigation capability in smooth terrains such that they increase the system performance in terms of cost and time. Therefore, the coordination and cooperation between robots with different navigation and sensing capabilities increase the efficiency of the proposed system in humanitarian demining operations.

Jacoby and Chang [64] were inspired from the hierarchical nature of military operational theory when developing a control methodology for heterogeneous networked unmanned ground vehicle and unmanned aerial vehicle teams for military applications. The ultimate aim of their research is to replace humans by effective autonomous systems in military missions. The proposed approach has an organizing schema about distributed networked robot teams applicable to hierarchical military rank structures. A new swarming concept within a military-like hierarchy is suggested in this work: simple small teams made up of two to four robots are constructed to accomplish a given mission while searching, tracking, carrying, and deploying abilities. This research provides a novel approach on the coordination control of networked robot teams in military field using the inherent benefits of control from emulating the distributive hierarchical nature of military operational theory.

3. Networked Mobile Robot System Design Issues

There are some desired characteristics of networked robot systems such as fault tolerance, scalability, adaptively controlled coordination, reconfigurability and communication. These issues are gaining importance in parallel with the increase of complexity of high level robotic tasks. Primary design factors particular to decentralized mobile robot systems are surveyed in this section.

3.1. Coordination Control

Coordination between robots means that they cooperate to achieve a given common goal. The usage of multiple robots has several advantages over single robot systems: cooperating robots have the potential to achieve a given task faster than a single robot by working in parallel [65]. Complex and high level tasks cannot be accomplished by a single robot even if they have high sensing and actuation capabilities. Moreover, the overall performance of the solution for a single robot system cannot be improved, while for a network of robot unit's coordination and cooperation enhance the efficiency of the system performance in terms of time, energy and data fusion [55,66].

In the literature, multi robot systems are categorized according to their coordination level, as fully coordinated, weakly coordinated and not coordinated. Coordinated robot networks are classified into centralized and decentralized [67]. Many control tasks are based upon the partitioning of the mission into different subtasks, which are then assigned to individual robots by a central unit or robot leader [68,69]. However, these systems do not handle the problem of distributing resources among robots. In centralized methods, a robot works as a 'leader' and group members send their acquired information to the related unit. The leader, in turn, plans optimal actions for each of the group members. In this case, robot units act only according to the leader's commands. Although in such cases coordination control of robots can be perfect and all the important information can be used by the team members, these methods are computationally hard and have a heavy communication burden [70,71]. An increase in complexity is proportional to the number of robots and this makes the usage of these systems difficult in real-time application. Moreover, these systems are not robust in cases of single point failures, and if there is a problem with the leader's abilities such as communication errors or physical crash, the task cannot be completed by any of the remaining robots.

On the other hand, in decentralized systems each robot unit is completely autonomous in the decision–making process [72–74] and executes a coordination protocol, while taking independent decisions. Since these systems are generally more robust to communication and group member failures, accomplishment of the task is not affected by a single point of failure, which gives the opportunity to use this architecture in real world applications [75]. However, disadvantages exist in distributed systems as well, such as integration of local task accomplishments towards a global aim. Moreover, all problems cannot be broken down into small tasks that will be assigned to separate robots.

3.2. Fault Tolerance

Any system that is not affected by a single point of failure (either in communication or in robot coordination by failure of some units) is called a fault tolerant system, which is a crucial property especially for decentralized systems such as networked mobile robots undertaking strategic and

complicated tasks. Homogenous centralized systems composed of robots with the same capabilities, both hardware- and software-wise, are more fault tolerant then heterogeneous ones since the failure of a robot member can be easily compensated by other network members that are identical to the failed one. However, homogenous systems cannot adapt themselves easily to complex and high level tasks where cooperation of different skills is required. This is the primary need for the emergence of heterogeneous robot networks.

Parker [76] introduced a pioneering work on the fault tolerant multi-robot coordination control method in heterogeneous robot networks. Each robot has overlapping capabilities with other team members and adapts its actions using sensory feedback from the execution tasks related with each robot's internal state and environmental conditions. Motivational behaviors are used to monitor task progress level and new tasks are dynamically distributed according to the state of the task accomplishment. ALLIANCE has been implemented on different multi-robot applications like box pushing and target tracking [77] and the validity of the method proven.

Another fault tolerant architecture (MURDOCH) was developed by Gerkey *et al.* [78] and the success of the proposed method is presented via box pushing experiments. An auction based task allocation system is proposed to intelligently coordinate networked robot team in noisy and dynamic environments. A publish–and–subscribe communication model is used for allocating tasks hierarchically to the robots. Some assumptions make their solution realistic in real world problem solutions: for example, any robot can fail at any time, communication between robots can crash or can be noisy, and a robot may not be aware of its own failure. Tasks are assigned to the most capable robot at every time step by a greedy task scheduler (MURDOCH) that guarantees the efficiency of that assignment through an auction process, which is performed with the following five distinct steps: task announcement, metric evaluation, bid submission, auction closing and progress monitoring or contract renewal.

Dias *et al.* [79] presented the Traderbots approach; a market based and robust multi-robot coordination methodology for in dynamic environments. Although an explicit communication strategy is used for task allocation, the proposed approach ensures the robustness of the team task execution by using failure recovery ability in the case of communication failures, robot deaths and partial robot failures.

Swarm approaches inspired from social insects such as bees, birds and bacteria, show robust coordination mechanisms to achieve a given global goal. Behaviors emerge from the local interactions among robots and the operation environment. Robustness is achieved as a graceful degradation of one robot member breaking down while another robot takes over the failed robot's task [80–82]. Although there is research into the fault tolerance of robot networks, there is no standard accepted metrics for evaluating this fault tolerance and this issue remains as an open research area.

3.3. Scalability

Scalability is one of the desired characteristics of robot networks. A robot network control strategy can be called scalable if the performance of the system does not decay by increasing the number of robots in the network. Existing networked robot research has only focused on small teams comprised of 5–10 robots. These networks have to be extended into large multi-robot teams in order to increase

the system performance and generate more robust solutions. Although simulation studies have been considered as a valid methodology, constructing reliable scalable mobile robots for developing simple, robust, efficient and low–cost robot platforms is crucial for accomplishing scalable real world robotic research [83–86].

Howard *et al.* [83] presented a potential field based distributed solution to the area coverage problem by using a mobile sensor network in an unknown environment. In this approach, robot units cooperatively work to cover the entire mission space by changing their initial configurations. This proposed method considers robot units as virtual particles where each of them is subject to virtual forces acting on each robot unit while being only dependent on the position and orientation of nearby robots and obstacles. This force is used as a control vector for each robot's motors. Robot units use only local information for decision–making, so there is no need for communication between robots. In this way, there is no need for environment modeling or localization. Hence the given methodology is highly scalable to large robot groups and the validity of the algorithm is demonstrated on a 100 robot deployment problem in a large and complex environment.

Balch and Hybinette [84] presented a scalable multi-robot formation control solution for homogenous large robot teams. Their method is based on a new class of potential functions, which are inspired from crystal molecules. At each time step, robots calculate a vector indicating the robot's navigation direction using parameters such as static obstacles, formation maintenance, movement to the given common goal and movement to the unit center. Each robot navigates towards a goal direction only with the help of location information of the nearby robots, so this given solution is completely scalable to large robot groups.

Nowadays, there has been remarkable research on human–robot interaction where scalability of the robots to the interaction in question has been a serious concern. Researchers have tried to develop systems to allow more effective communication between humans and robots in the education, rehabilitation, and museum tour applications with scalable tasks adaptive to interactions. Tews *et al.* [85] proposed a scalable interaction infrastructure for the human–robot interaction problem. This infrastructure consists of two characteristics phases: one of many–to–many interactions and the second of one–to–one interactions. The first phase is required to expose robot services to human beings and the second one takes place in the level of personal one–to–one interaction. The proposed approach allows many humans to interact with many robots by dividing requests while also undertaking one–to–one interactions. Although multi-robot and multi-person systems are introduced by Tews *et al.* much of the current work is focused only upon single robots and single human beings and scalable approaches for human–robot interaction is still an open area of research.

Reconfigurable modular robots also need scalability capability, because scalability provides high level task accomplishment capability to the robot with the help of a large number and complex modules. Kurokawa *et al.* [86] constructed a reconfigurable modular robot called M-TRAN. The proposed mechanism can perform flexible and adaptable locomotion by acting as a four-legged robot or a snake-like one. Developments of local infrared communication between neighboring units and of parallel distributed motion control mechanisms make this method highly scalable, thus adaptable and dexterous.

Generally, reconfigurability of robot team boosts the complexity of the system. Thus, scalability becomes out of the question due to this complexity issue. Therefore, more work is still needed to consider the literature tackling reconfigurable and scalable networked robots.

3.4. Holonic Reconfigurability

Robotic researchers have always shown interest towards reconfigurable and scalable distributed robotic structures. Holonic reconfiguration was the early attempt in reconfigurable and scalable networks. Holons, introduced by Hirose, usually work in cooperation with other holons of a group, forming a modular flexible system [87]. The basic property of a system having a holonic architecture is that it is built from simpler components working in a colony so as to achieve a global behavior of a higher order [87,88].

In holonic robotic structures, the overall system behavior is determined not only by the individual autonomy of each primitive robot subsystem that forms the whole structure, but also by cooperation between those subsystems. Distributed decision–making and control yield the capability of cooperation in such systems. Many works exists in the literature using modular systems that pertain to the principle of independence and cooperation, although not all of them are called as holonic.

Chen and Burdick [89] studied the optimum configuration of assemblies built up from modular robots for a given task. They consider kinematic geometry joined by joint elements. The optimum task oriented kinematics is obtained using genetic algorithms due to the discrete nature of the problem. Ueyama *et al.* [90] focused on the robotic systems called CEBOTs (Cellular Robotics Systems), which are functionally different robots that work together to achieve a given task by sharing subtasks. They make use of Genetic Algorithm in the trajectory planning of each module called a cell.

Chirikjian [91] designed his own modular robotic system and produced a few prototypes. The main points in his work are the strong coupling between the modules, producing stiff structures that can also accomplish reconfiguration. Because of the self–reconfiguration ability of these systems, he calls them "metamorphic". These modules are designed in a hexagonal geometry due to fact that symmetry brings a great simplification to the analysis and control of self–reconfigurable systems. Chirikjian used the simulated annealing method to decide on the action of each module in the reconfiguration phase. Similar to Chirikijan, Murata worked on the self–reconfiguration of modular structures made up of symmetric modules. Since their hexagonal symmetric structure is similar to fractal structures, he calls each of the modules a "fractum" [92]. As is also the case for the metamorphic robots of Chirikijan, fractums move within the structure by "sliding" over each other. In both of the works [91,92], the coupling principles of the modules are the same and are based on electromagnetic fields.

The need for holonic systems arises from the unstructured nature of the media where the robot has to operate and from the changing nature of the task in that medium. In order to adapt such a medium, the system must change its structure in an optimum way so that a variable structure is achieved in the control and task spaces while keeping itself robust and accurate in behavior [93–95]. Cooperation of robot units towards reconfiguration of the distributed robotic system can only be feasible under seamless uninterrupted communication.

3.5. Communication

Communication between robot units in the network is essential for real world applications because of situational awareness. In particular, cooperation and coordination in networked systems requires a robust communication ability to accomplish a given mission accurately. Communication methods in networked robot systems are classified as implicit communication, also called stigmergy, and explicit communication. The effect of communication on the system performance is shown in a variety of works; non–verbal communication efficiency in human–robot teamwork [96], target search task performance evaluation with no communication, reflexive and deliberative communication [97], communication range effects on robot search task on two distinct search algorithms which are spiral search and informed random search [98]. Çayırpunar *et al.* [98] developed a cooperative search method in complex environments and shows the effect of communication in the target search mission on real experimental setups. In these experiments, e-puck robots try to find a hidden object via explicitly communicating with their local neighbors. They concluded that the system performance improves with increasing communication range, in terms of the task accomplishment time. Robots can exchange information about the other robots' internal states and environmental conditions via explicit communication protocols, which also improves the system performance. Meanwhile, this yields a considerable computational burden to the robot team and these systems may not be robust to single point failures.

Explicit communication is achieved using special standard communication protocols. Environmental conditions are important for explicit communication especially in indoor applications such as search and rescue operations; reliability and robustness may be corrupted due to noisy or failed signals in explicit communication techniques as seen in some special cases of references [99]. For example, in a semi–collapsed building, communication signal strength can be very strong only until one meter, whereas in outdoor environments, communication signals can generally easily cover 50 m with full bandwidth. Explicit communication approaches are also not suitable in the sense of scalability characteristics because of communication load and computational complexity [76].

In implicit communication techniques, information transmission is accomplished through the environment or via the observation of robot behaviors. Implicit communication based approaches were first introduced by Balch *et al.* [84], who showed that there is no need for explicit communication in some task executions. Their communication strategy is inspired from biological systems such as social behavior of animals, and they proved that explicit communication is unnecessary in graze tasks. Although implicit communication is simple, it can suffer from limitations in robots sensing abilities.

Swarm robotic researchers have focused upon implicit communication to obtain emergent cooperation. This provides the opportunity for the colony's control algorithm to be scalable to large numbers. Anderson and Papanikolopoulos [100] presented an implicit cooperation methodology for networked robots search in unknown areas with a reactive, layered architecture composed of three behaviors; namely, obstacle avoidance, stall recovery, and search. Each robot selects its next search area in the border of a locally sensed area so the algorithm bases upon local experience rather than the collective experience. It is proved that selection of local search goals increases the system performance, because it reduces interference between robots.

Implicit communication between humans and robots in heterogeneous teams is extremely important in order to understand the internal state of the robot. Breazeal *et al.* [96] introduced such an implicit non–verbal communication technique between robot and human by using behaviors, social cues and gestures, without any deliberate communication. The research platform, Leonardo, allows the human to maintain an accurate mental model of the robot with its social cues. This gives an opportunity for humans to coordinate their activities with those of robots. Communication in the future of networked mobile robotics tends towards distributed cognition, interpreting social behavior and intention recognition of subparts of the networking.

4. Hybrid Sensor Network

Hybrid sensor networks consist of static and mobile units working together to achieve a given common goal. Static nodes are used to collect data about the physical environmental conditions or to detect events, while mobile nodes are used to build upon acquired data for a more detailed analysis of the environment or to improve coverage by using their mobility capability. Collaboration and coordination between network units increase the efficiency of the task execution in networked hybrid sensor based systems. Coverage of very large areas has become an important issue for static sensor networks because of their limited number of static nodes, sensor failures due to limited energy or environmental conditions, and heterogeneous sensor distribution caused by random sensor distribution over the area. To reliably accomplish missions, especially in large and irregular regions, a huge number of sensor nodes are necessary, which is not always feasible with the current technology. Mobile nodes have to be used to improve area coverage and enhance sensing and communication abilities of the overall sensor network in the area of interest. Lambrou and Panayiotou [101] presented area monitoring methodology by using hybrid wireless sensor networks with stationary and mobile nodes. Mobile robots collaborate with the stationary nodes so that they navigate towards areas that are the least covered by the stationary sensor nodes. Static sensors work as pathfinders for mobile ones and undetected targets can be detected via improved coverage. However, in this approach, mobile robots cannot control their actions according to the other mobile units' navigation paths, so multiple area coverage occurs and energy efficiency is considerably decreased.

Viet *et al.* [102] proposed a distributed hybrid sensor network control algorithm to increase the efficiency of event detection in a given sensing area, based on the minimization of total energy consumption. In their work, static sensors completely cover the area of interest and can detect all extraordinary actions. After the detection of events by static sensor network, mobile sensor units are sent to event–related locations to identify the details of the event. Static sensor localization is very important in hybrid networks: they are randomly deployed in the environment by using airplanes, therefore, mobile robots are used to localize static sensors via signal strength of received radio messages [103]. The localization problem is solved by the Robust Extended Kalman Filter (REKF) based state estimator, which is more efficient then the classic Extended Kalman Filter (EKF) in terms of computation cost and robustness. The accuracy of the proposed methodology has proven to be approximately one meter, which is very good when compared to other methodologies that use received signal strength.

However, combining static sensor networks with mobile sensor networks shifts the load of correcting the heterogeneity of the coverage inherent to static subnetworks, to the nodes of the mobile subnetwork. This compensation that is required from mobile sensor networks increases the energy need, thus tremendously decreasing energy efficiency. Wearable or sticking wireless sensor networks (WSN) on different carrying agents are now appearing in the literature [104,105] in order to handle energy inefficiency. All these wearable WSN approaches aim to get human centered data from the human himself or herself and his/her environment under his/her knowledge. In such wearable WSNs, it is assumed that the sinks, which are the final destinations for the data collected, are within the wireless range, *i.e.,* that they are connected [105,106]. In systems such as transporter deployment architectures, the static network has an infinite energy source and the WSN is able to connect to distant nodes like satellites [107]. Doğru *et al.* [108] aimed to generate network structures that have the ability to control coverage while still being static sensor networks. Giving the ability of controlled deployment to static sensor networks may appear as a true controversy but the authors develop and implement their novel concept of static sensor subnetworks that are equipped with limited mobility by using only clandestinely the mobility of an agent they hook parasitically upon. They term such networks Sycophant Wireless Sensor Networks, in short SWS networks. SWS networks are clandestine travelers that passively use without hostility the mobility of the carrying agent, to collect, process, and communicate data harvested during the agent navigation about its environment, and not necessarily about the agent itself as classical wearable sensor networks do. This SWS networks cannot in any circumstance guide or influence the motion of the carrying agent. Agents perform their navigation for each task without the knowledge of the onboard "clandestine" SWS network. The proposed work also contributes to advancing the hybrid static and mobile sensor network usage found in the literature by the novel hybrid approach of SWS networks cooperating with Sparse Mobile Sensor networks in Simultaneous Localization and Mapping (SLAM) of a region. Map growing is being accomplished by the cooperation of different types of nodes; those of the SWS network and those of the sparse mobile sensor network.

5. Conclusion: Future Challenges in the Networked Mobile Sensor World

In light of the above–presented work addressing existing research, there are many significant challenges for the future of networked mobile sensors. In this section, we briefly present some of the key important open research questions and develop a roadmap for the networked robot network area extrapolating into its future.

The European Robotics Technology Platform (EUROP) published a Strategic Research Agenda (SRA) on 7 July 2009 for robotics researchers to attract attention to key challenging robotic topics and to promote robotic development in Europe [109]. Human–robot interaction is a very challenging research area. Because existing works are still very new and immature, most of the developed systems are not yet able to perform outside simple laboratory experiments. Existing works only focus on single human and single robot problems, so scalable approaches for human–robot interaction is an open research interest to be tackled in the near future. Human–robot learning interfaces, which enable humans and robots to communicate with each other, have to be constructed utilizing cognitive approaches. If many humans interact with networked robots, a distributed learning interface, excited at

any different instant of time, at different locations of robot units and human units, will be one of the challenge of cognition.

Cooperating robots in a distributed manner is another field of research where desired global behavior emerges from the interactions between robots and environments. Distributing and assigning tasks is crucial in order to improve the efficiency of the robot network in real-time and dynamic environments. Thus, scalable and fault tolerant coordination control algorithms with effective local or implicit communication are important to obtain real-time responses by fusing obtained data from reduced communication loads.

Physical construction of networked robots that can operate under hard and real-time conditions is an opportunity for future robotic research. In particular, reconfigurable robots, in which robot units are connected to each other physically, will inject real-time control to swarms that are mainly exhibiting emergent behaviors nowadays. Wireless communication protocols need to be improved for efficiency in strategic missions such as search and rescue. Reconfigurable heterogeneous robotic systems can adapt their structures to the changing environmental conditions and needs, such as changing the robot configuration from a legged robotic structure to a snake robot and then to a rolling robotic one [110]. Reconfigurable networked robot systems are fault tolerant in the case of robot failures by replacing faulty part autonomously. Self–repairing reconfigurable robots will tend towards self–repairing hybrid networks composed of fixed sensors, computing devices, human operators and robot teams is currently a trendy worldwide research topic. With the help of synergy between these different operation units, the overall performance of the system can be increased in complex and high level tasks. Cooperation between biological and mechanical networks with human beings will present the "avatarization" of networked robotics in the long-term future of research.

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