Active Sensing with Mobile Sensor Networks: A Survey

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***Abstract*—Mobile sensor networks are distributed collections of nodes, each of which has sensing, computation, communication capabilities, while some of which have locomotion capabilities. Mobility enhances the efficiency and accomplishment of sensor network. Controllable mobility can help sensor network perform active sensing. The paper presents an extensive survey of controllable mobility for active sensing of mobile sensor network in various research areas such as mobile sensor network localization, simultaneous localization and mapping, area exploration, area coverage, target detection and tracking and monitoring of spatio-temporal dynamics in large environments.**

***Index Terms*—mobile sensor network, mobility, active sensing**

I. Introduction

DEVELOPMENT/ of MEMS technology, digital electronics and wireless communication technology makes it possible to assemble sensor network for information seeking [1], [2]. Comparing with a single sensor, the obvious advantages of sensor networks include relatively lower costs, complementary heterogeneous sensing, inherent robustness, and greater coverage area. Moreover, mobile sensing platforms, such as, unmanned aerial vehicles, underwater robots, and autonomous ground vehicles, can autonomously and purposefully move to collect interested information in harsh environments where are inaccessible to human. Mobility enhances a number of useful capabilities for sensor networks in many applications ranging from search-and-rescue in urban ruins, environment monitoring, to target detection/tracking in large environmental space and military surveillance systems in dynamic battlefields. Mobility can improve the efficiency of data collection, adapt to unpredictable changes in the dynamic environment and network itself, and provide robust responses to individual failures. The architecture of typical mobile sensor networks is shown in Figure 1.

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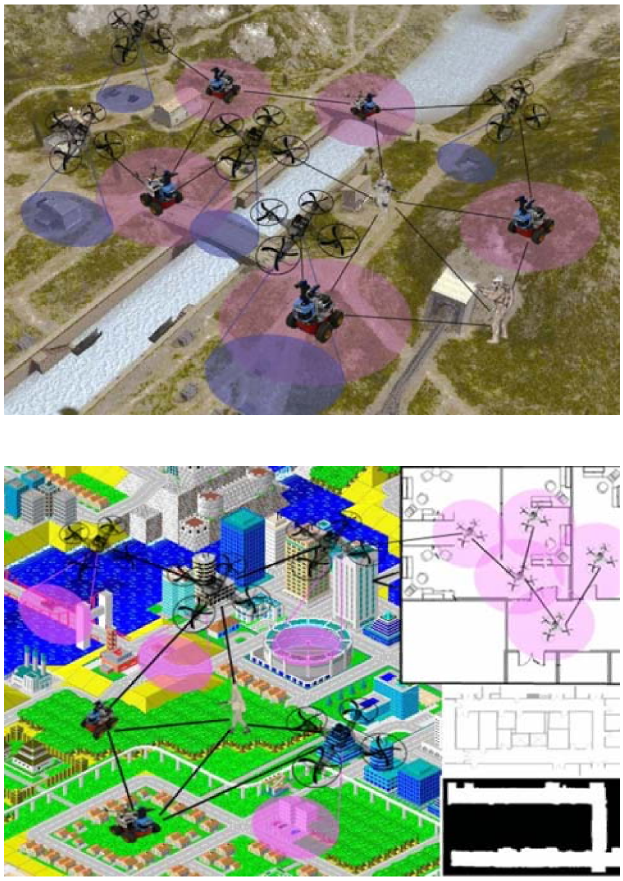

Fig. 1. Architecture of typical mobile sensor networks

The task of mobile sensor network can be generalized as information acquisition no matter for whatever applications, such as feature localization, mapping, target detection and tracking, area coverage, area exploration and so on. For some applications, mobility is one of the necessary abilities for sensor nodes to fulfill their sensing tasks, for example, search-and-rescue, simultaneous localization and mapping, area exploration, especially for large environments with a very limited number of sensors nodes. For the other applications, such as, area coverage, target detection and tracking, mobility can drastically improve the efficiency of completing sensing tasks and

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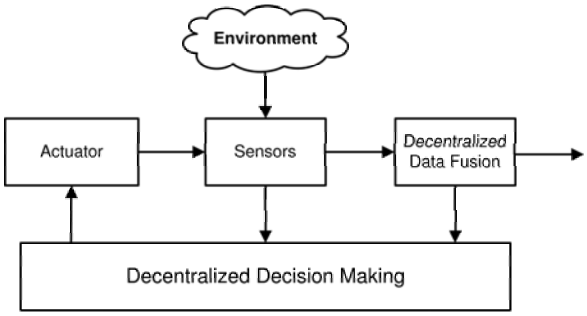

Fig. 2. Structural diagram of decentralized active mobile sensor network

help optimize the precious communication and energy resources. By means of controllable mobility, mobile sensor network is expected to be able to perform active sensing or active perception [3]. Trajectories of mobile platforms are intentionally and adaptively scheduled for more reliable and accurate information acquisition of the interested dynamic physical environments with more effective resource utilization.

However, mobility requires extra energy cost. This would decrease the energy efficiency. And there are many other factors which should be considered for designing the optimal trajectories maybe conflict with each other. For example, in area exploration applications, the mobile sensors should go to unknown area for new area exploration; whereas, the sensor nodes should visit the known area for improving the accuracy of localization and mapping. In area coverage applications, mobile sensors should spread out as widely as possible for greater area coverage; whereas, the nodes should stay close enough for reliable communication and fault tolerance. Moreover, each sensor node has limitations in sensing, computation capability, power, communication bandwidth, and locomotion constraints. Mobile sensor networks have to experience uncertainty in motion processes, sensor measurements, communication channels and dynamic complex environments in practical applications. If scalability, robustness, fault tolerance and timeliness are taken into account, decentralized framework is the inherent choice for managing mobile sensor network resources and coordinating mobile nodes' motion. Therefore, active sensing by means of controllable mobility for decentralized mobile sensor network is a very challenging task.

The structural diagram of decentralized active mobile sensor network is shown in Figure 2. Each mobile platform in the network has four blacks: sensors, actuator, data fusion and decentralized decision making block.

1) Sensors: Each platform has one or more sensors. These homogeneous or heterogeneous sensors can acquire redundant or complementary measurements from environments. The measurements are processed at its local data fusion block with information transmitted from its neighbor nodes.

2) Data fusion block: Aiming at dealing with uncertainty in the mobile platform's model and the sensor's model, data fusion block fuses local measurements with measurements or estimates transmitted from its neighbor nodes to update its local estimates of the interested targets in the environment by using some state estimation techniques. The estimates are passed to the decentralized decision making block.

3) Actuator: With actuator, mobile platform can move autonomously. The actuator controls the direction and velocity of the mobile platform. It receives the control instructions from the decentralized decision making block.

4) Decentralized decision making block: Based on the knowledge of local node capabilities and the estimates of environment, decentralized decision making block determines local decisions about mobile platform's next motion with considering sensing, communication, and energy resources optimization by optimizing some criterions, which are some functions of both utilities and costs, and then sends control instructions back to the actuator. With the feedback control from decentralized decision making block, mobile sensor network should be able to fulfill active sensing, that is, adaptively plan motion trajectories of mobile platforms to implement appropriate information acquisition meanwhile sensing, communication, energy resources saved and utilized effectively.

Many researchers have studied controllable mobility for active sensing of mobile sensor networks in many application fields. This paper will overview the state-of-the-art research on controllable mobility for active sensing of mobile sensor networks in terms of the corresponding applications: mobile sensor network localization (the pose of the sensor network platform itself) in Section II, simultaneous localization and mapping (the pose of the features in the environment and the pose of the sensor network platform in the map of environment) and area exploration in Section III, area coverage in Section IV, target detection and tracking (the position and velocity of targets) in Section V, perimeter detection and tracking in Section VI, and monitoring of spatio-temporal dynamics in large environments (such as the water quality monitoring in rivers and lakes, the forecast of weather) in Section VII. Finally, conclusions are given in Section VIII.

II. Mobile sensor network localization

Localization is an important issue for mobile sensor network in many applications, such as environment monitoring, target tracking and intrusion detection. The locations information of sensor nodes are needed to label the data for recording where they are collected. It can help save energy for route discovery [4] and enhance security for ad hoc sensor network [5].

Mounting a GPS receiver on each mobile sensor is a matter-of-course solution for mobile sensor network localization problem. Unfortunately, even if low-cost GPS can be commercially available now, the straightforward solution of adding GPS to all sensor nodes is not practical since GPS cannot work indoors or in the presence of obstacles that limit line-of-sight to the satellites. Additionally, the GPS signals may be jammed and become unavailable in some hostile scenarios such as battlefield surveillance [6]–[9]. Due to the limitations of GPS, numerous localization techniques have been proposed for wireless sensor networks.

Wireless sensor network localization techniques may be classified into: *anchor-based techniques* computing a large number of common sensor nodes' positions with a few of anchors or seeds whose locations are known with GPS or other additional locating devices [7], [10], [11], and *anchor-free techniques* for situations where an infrastructure does not exist and GPS cannot be used [12]–[14]. According to the method of whether to use range information, the localization algorithms can be divided into two categories: *range-based* and *range-free*. The former depends on range (distance or bearing) measurements from special hardware [15]–[17]. It provides more accurate position estimates than the latter which makes no assumption about the availability of range measurements [18], [19].

Mobility has been exploited for wireless sensor network localization. Mobile seeds have been used to help common sensor nodes obtain their location estimates [10], [20]–[22]. Moving in the sensing field and broadcasting their current position information periodically, one mobile seed plays as several virtual static seeds thus decreasing the cost for seeds. Mobility has also been exploited by Monte Carlo Localization (MCL) which is specially proposed for mobile sensor network [23]–[25]. Random motion of nodes are typically assumed.

Naturally, localization algorithms for static sensor networks can be extended to mobile sensor network by rerunning periodically after some time interval, which is either static or adaptable, to support mobility. However, it will incur high communication/computation cost.

Bergamo and Mazzini first consider localization with mobile nodes [26]. There are two beacons fixed in known positions to transmit across the entire network. Each sensor node can derive the actual distance between it and the beacons according to the signal strength from the two beacons. The position is obtained by means of triangulation. Although they consider the sensor mobility, their research studies how mobility makes localization more difficult and shows that errors increase with increasing node speed instead of using mobility to improve localization.

Actually, mobile seeds have been used in static wireless sensor networks to help improving the accuracy of localization [10], [22], [27]. With mobility, one seed can serve as more virtual seeds. More sensor nodes can benefit from the mobile seeds' position broadcasts.

Although mobile sensors have a chance to get more information, mobility increases the uncertainty of nodes' positions. The challenge for mobile sensor network localization is to let the wireless sensors benefit from mobility and not only suffer from it.

Localization algorithms specially designed for mobile sensor networks have come forth after Hu and Evans first applied Monte Carlo Localization (MCL) for mobile sensor network localization [23]. All of them are based on Sequential Monte Carlo (SMC) methods. The posterior distribution of a sensor node's position after move can be naturally formulated using a nonlinear discrete time model and the SMC method provides simple simulation-based approaches to estimating the distribution. The posterior distribution of a common node's position is represented by a set of weighted samples in SMC-based localization methods. With SMC localization methods, sensor nodes can benefit from mobility and exploit mobility to improve the efficiency of localization and get a better accuracy of its position estimates.

SMCL algorithms either suffer from low sampling efficiency or require high seed density to achieve high localization accuracy. Mobile nodes typically are assumed to have little or no control of mobility and cannot detect their speed and direction. Only the maximum speed is known and uniformly distributed. The sampling efficiency is low due to the mobility uncertainty. It is necessary to improve the sampling efficiency to reduce the computational cost for sensor nodes which usually have limited computational capability. High seed density can improve localization accuracy. However, beacon nodes are much more expensive than common sensor nodes. Some researches have been done to improve sampling efficiency and improve localization accuracy with limited number of seeds.

A brief description of the major researches on exploiting mobility for improving the accuracy and efficiency of mobile sensor network localization is presented as follows:

A. Prediction of position based on mobility

The basic idea of SMCL algorithm is that exploiting mobility for mobile sensor network localization. A set of samples which represent a sensor node's possible position after move is predicted with nonlinear discrete time dynamic motion models in the prediction step of the simulation-based SMCL algorithms [23]–[25], [28].

Due to harsh aqueous environments, non-negligible node mobility and large network scale, localization for large-scale mobile underwater senor networks is very challenging. Zhou et al. find a very useful property that underwater objects move with predictable patterns which are in a large part determined by environmental factors. By utilizing the predictable mobility patterns of underwater objects, Scalable Localization scheme with Mobility Prediction (SLMP) is proposed [29]. Anchor nodes with known locations in the network conduct linear prediction by taking advantages of the inherent temporal correlation of underwater object mobility pattern. Each ordinary sensor node predicts its location by utilizing the spatial correlation of underwater object mobility pattern and weighted-averaging its received mobility from other nodes.

B. Improve sampling efficiency based on mobility

In the prediction step of SMCL algorithm [23], a sensor node randomly chooses a set of samples representing the belief of the node regarding its location within the deployment area, only constrained by its maximum speed and the previous location samples. Information about one-hop and two-hop anchors are used at filtering step only for rejecting impossible samples. Drawing samples is a very tedious process.

Monte Carlo Localization Boxed (MCB) algorithm uses information about the anchors in the prediction step to reduces the candidate samples area with a bounding-box [30]. The information about the anchors heard is used to build an anchor bounding box for a node to draw samples within the region it covers.

Weighted MCL (WMCL) algorithm further reduces the average size of the sensor nodes' bounding-box constructed in MCB by using two-Hop beacon neighbors' negative effects and sensor neighbors' estimated position information [25].

Sample Adaptive Monte Carlo Localization algorithm (SAMCL) adaptively determines the number of samples based on the number of beacon nodes heard [31]. If many beacon nodes are heard, only a small number of samples are needed to characterize the distribution of the sensor node's position to reduce the computational cost.

C. Increase localization accuracy with mobility

A sensor node only uses messages from its beacon neighbors within two hops as its observation in MCL [23]. More information can be used as observation to improve localization accuracy. In MSL* and MSL (Mobile and Static sensor network Localization) algorithm, a sensor node uses all its neighbors including beacon nodes and sensor nodes within two hops for localization [28]. Their sampling strategy is different from that of MCL to decrease the computational cost. Samples in last time unit could be reserved in the current time unit. MSL* is more suitable for sensor networks where nodes move slowly.

Moreover, the authors consider how different mobility models affect the localization accuracy. Reference Point Group Mobility model (RPGM) [32] is used to investigate the effect of group behavior on localization accuracy. The research result shows that the accuracy is substantially reduced when the group motion dominates the individual node movement. And a strategy that moves seeds in a way to cover the area thoroughly will improve the accuracy, and especially the convergence time of MCL. In their research, sensor nodes move randomly without considering other mobility patterns. The drawbacks of MCL are: it needs a high density of seed; and the sampling technique it uses generates high computation burden. MCL requires that sensors need to move with at least a predetermined minimum speed. Based on Hu and Evan's work, Baggio and Langendoen present Monte Carlo localization Boxed (MCB) algorithm to improve the sampling efficiency by using bounding-box to restrict the scope from which the candidate samples are drawn [24]. Their work also assumes the random movement without discussing extra information on the sensors' mobility patterns and mobility-pattern variability.

In MCL, a sensor node uses its anchor neighbors within two hops to compute its location. The localization accuracy can be improved by using more information. MSL (The Mobile and Static sensor network Localization) and MSL*, two fully range-free localization algorithms, use the location estimations of all neighbors (not just seeds) to improve location accuracy [28]. MSL* and MSL exhibit graceful degradation in performance with decreasing seed density. MSL* and MSL can achieve higher location accuracy than SMCL. However, they need high node density and high anchor density to converge. The two methods need to use more communication and computation at the sensor nodes. The two methods are more appropriate for large sensors that can support the extra communication. Movement of sensors is also implemented using a modified version of random waypoint mobility model [33].

Yi et al. also consider mobile sensor network in which anchor nodes and sensor nodes are moving randomly with random waypoint model [34]. Their research assumes that anchor nodes know not only its position but also the global time of the moment when the anchor obtains its location and there are sufficient number of anchor. Anchor node informs its position to nearby unknown nodes. The anchors' clocks are synchronized. The sensor nodes receive beacons from nearby anchors. A history of anchor information is used to characterize the mobility of sensor nodes. The sensor node then calculates its new position with the movement models using a regression model in real time. Thus, an efficient localization algorithm can be developed by using the predictable pattern of mobility.

Mobile anchor nodes are used for range-free localization [10]. Each anchor node equipped with the GPS moves in the sensing field and broadcasts its current position periodically. The sensor nodes obtaining the information are able to compute their locations. One mobile anchor node can play as several virtual static anchor node. Thus, the cost for anchor nodes can decrease.

Zhang et al. consider a mobile sensor network in which both the seed nodes and sensor nodes can move [25]. Existing localization algorithms for mobile sensor networks are usually based on the Sequential Monte Carlo (MCL) method. They either suffer from low sampling efficiency or require high beacon density to achieve high localization accuracy. An energy efficient algorithm, Weighted Monte Carlo Localization (WMCL), which can achieve both high sampling efficiency and high localization accuracy, is proposed. Besides MCB algorithm [24], further reduces the size of the bounding-box constructed in MCB by using two-Hop beacon neighbors' negative effects and sensor nodes' estimated position information to achieve high sampling efficiency. By using estimated position information of sensor nodes, WMCL greatly improves the localization accuracy. The iterative WMCL (IWMCL) algorithm iteratively execute WMCL with different assumptions on the nodes' speed. IWMCL can dramatically improve localization accuracy when nodes move very fast.

The above localization algorithms assume that all the mobile nodes are modeled by the modified version of random waypoint mobility model [33]. The mobile nodes only know their maximum speed.

D. Control the frequency of localization based on sensor mobility behavior

No matter with either range-based schemes or range-free protocols, the more often the localization, the more accurate the location estimate. However, the localization frequency should be minimized to decrease the scarce energy consumption. Tilak et al. investigate adaptive and predictive protocols that control the frequency of localization based on sensor mobility behavior to reduce the energy requirements for localization while bounding the localization error [35]. Two algorithms for dynamic localization are presented. DVM (Dynamic Velocity Monotonic) adaptively matches the localization period to the observed velocity of the node. MADRD (Mobility Aware Dead Reckoning Driven) uses dead reckoning to predictively estimate the location of a node assuming it is following its recently tracked trajectory. The random waypoint mobility model is used.

E. Static wireless sensor network localization with a moving Location Assistant

Zhang et al. investigate the sensor network localization problem from a novel perspective by treating it as a functional dual of target tracking [36]. In traditional tracking problems, static location-aware sensors track and predict the position/velocity of a moving target. As a dual, a moving Location Assistant (LA) (with a GPS or a predefined moving path) is utilized to help location-unaware sensors to accurately discover their positions. The proposed system is called Landscape. In Landscape, an LA (an aircraft) periodically broadcasts its current location beacon while it moves around or through a sensor field. Each sensor collects the location beacons, measures the distance between itself and the LA based on the received signal strength (RSS), and individually calculates their locations via an Unscented Kalman Filter. The Landscape scheme has several advantages, such as high scalability, no intersensor communication overhead, moderate computation cost, robustness to range errors and network connectivity. Their research limits to the localization of a static sensor network. Priyantha et al. presents mobile-assisted localization (MAL) scheme for wireless sensor network [22]. A robot wanders through an area to collect distance information between the nodes and itself until these distance constraints form a 'globally rigid' structure that guarantees a unique localization. This localization method does not need anchor nodes. However, this method is end-to-end method. It can not run in real-time.

F. Mobility scheduling for mobile sensor network localization

Researchers have recognized that the trajectories of mobile seeds have a great influence on localization accuracy. Sichitiu et al. first brought up the interesting question that what the optimum beacon trajectory is [21]. They acknowledged the difficulty in selecting an optimal trajectory for the beacon. However, any specific path planning method has not been provided. In [37], their work showed that localization precision was good and uniform as long as the seed trajectory covered the entire deployment area in such a way that each point received at least three non-collinear seed messages. In [23], the authors also found that moving seeds with a predefined path that maximizes coverage can improve the localization accuracy of common sensor nodes and decrease the convergence time. Ssu et al. implicitly studied the path planning problem of the mobile beacon [10]. Sensor nodes track the series of beacon broadcasts and only use the non-collinear one to localize. The mobile beacon is assumed to move randomly. Koutsonikolas et al. studied three different trajectories for the mobile beacon, namely SCAN, DOUBLE-SCAN, and HILBERT. Their work showed that a carefully selected deterministic trajectory that all sensors could receive seeds' messages can significantly reduce the average localization error, compared to random movement [38]. Huang et al. designed additional fixed paths that reduce the collinearity, that is, CIRCLES and S-CURVES [39]. Xiao et al. conceived two straight-line movement patterns of the beacon: the Sparse-Straight-Line movement, the Dense-Straight-Line (DSL) movement [40]. The beacon travels along predefined straight lines and turns at right angles. Their work showed that the distance and route that a beacon travels seriously affect the localization accuracy of sensor nodes. Based on the performance study on tessellation (triangular, rectangular, and hexagonal) of beacon locations [41], Iqbal et al. studied optimal beacon movement strategy to guarantee the expected maximum localization error within a user-defined bound [42]. These static path planning methods needed a prior knowledge of the deployment environment.

Few existing works addressed the beacon mobility dynamic scheduling for wireless sensor network localization. Priyantha et al. designed a movement strategy for a mobile robot which was used to assist in measuring the distances between static node pairs until a globally rigid structure that guarantees a unique localization was formed [22]. The mobile robot has to discover each node, one-by-one, and move around it to measure distances. The traversal path of mobile beacon is long. Under strong assumptions that accurate pair-wise distance measurements can be obtained, a movement strategy of mobile beacon for range-based localization was proposed [43]. Trilateration method which requires three non-linear reference locations is used for localization. Upon the request of sensor nodes, beacon moves to preferred regions to provide sensor nodes reference locations. If there is no request received, the beacon do not know where to go.

Li et al. studied dynamic beacon mobility scheduling for implementing a full localization and proposed a deterministic beacon mobility scheduling without requiring any prior knowledge of the sensory field [9], [44]. The algorithm is deterministic in the sense that sensors's visiting order is fixed if the beacon starts from the same sensor. Beacon trajectory is defined as the track of depth-first traversal (DFT) of the network graph. The mobile beacon performs DFT under the instruction of nearby sensors on the fly. It moves from sensor to sensor in a heuristic manner according to distance measurements. The beacon moves a few step to a position closer to sensor node without resorting to the position information. With sufficient beacon signals received, each sensor node localizes themselves. Topology control (LMST: Local Minimum Spanning Tree) is applied to shorten beacon tour and reduce delay. DFT and LMST incur expensive computation complexity. In [45]–[47], the next position of mobile beacon is narrowed down to six possible positions based on geometry. Quality of neighbors (QoN) is used as for choosing the walking direction of the mobile beacon. The unknown sensor with most neighbors has the best chance to be the next target of the mobile beacon. While the coverage rate can be improved without requiring a prior knowledge of sensory field, localization accuracy has not been taken into account directly.

III. Area coverage

The efficiency of sensor networks depends on the coverage of the monitoring area. Adequate area coverage on the field of interesting is very important for sensor networks to fulfill sensing tasks. Area coverage can be classified into two groups according to the objective of area coverage: static area coverage and dynamic area coverage. Static area coverage is aiming at the end static configuration. Dynamic area coverage is aiming at the area coverage in a time interval.

Mobility can improve coverage of sensor networks, especially for unknown or hostile environment, such as harsh fields, disaster areas and toxic urban regions. In a sensor network with locomotion facilities, sensors can move around to self-deploy. Many movement strategies for improving network coverage in wireless sensor networks have been presented [48], [49].

A. Static area coverage with controllable mobility

Mobile sensors are controllable to move to the desired positions in order to maximize network coverage [50]–[55]. The algorithms can adapt to changing environments and re-compute their desired locations accordingly. Their common objective is to exploit mobility to obtain a new stationary configuration according to changing environments that improves coverage after the sensors move to their new desired locations. Their differences mainly lie on that how the desired positions of sensors are computed.

An incremental deployment algorithm is proposed to deploy sensor nodes one-at-a-time into an unknown environment, with each node making use of information gathered by previously deployed nodes to determine its deployment location [52]. At the end, this algorithm maximizes network 'coverage' while simultaneously ensuring that nodes retain line-of-sight relationships with one another. However, it has expensive computation and fragile to sensor failure.

A potential-field-based algorithm is proposed in which nodes are treated as virtual particles subjected to virtual force [51]. The virtual forces repel the nodes from each other and from obstacles to ensure the initial configuration of nodes quickly spreads out to maximize coverage area. A virtual-force-based sensor movement strategy is also proposed to enhance network coverage after an initial random placement of sensors [50]. The virtual force of a sensor is directly derived using the distance between the sensor and the other sensors and obstacles. A combination of attractive and repulsive forces is used to determine virtual motion paths and the rate of movement for the randomly-placed sensors. The computation time is negligible. After the execution of the algorithm and once the effective sensor positions are identified, a one-time movement is carried out to redeploy the sensors. Artificial potential field based algorithm is also used for area coverage with the constraint that each of the nodes has at least K neighbors where K is a user-specified parameter [56]. Artificial potential field based algorithm is distributed, scalable, and does not require a prior map of environment.

After initial random deployment, Voronoi diagram is used to discover the coverage holes (the area not covered by any sensor) and three movement-assisted sensor deployment protocols, VEC (VECtor-based), VOR (VORonoi-based), and Minimax based on the principle of moving sensors from densely deployed areas to sparsely deployed areas are designed to increase the coverage [53]. All of the above proposed algorithms spread sensors in the field to obtain a stationary configuration such that the covered area is maximized.

A peer-to-peer model based on Delaunay Triangulation and Voronoi diagrams is presented to define the geometrical relationship between sensor nodes [57]. The distributed model allows formal analysis for the fusion of spatio-temporal sensory information of the network. Taking into accounts with the environment constraints, the presence of obstacles and the nonholonomic constraints of the robots, the system can be reconfigured with the distributed algorithm so that the covered area can be enlarged.

Most of the works consider networks where the nodes' sensing footprints are node-centred circular ones. [49] considers the case where a node's sensing region is approximated as any arbitrary convex set. A distributed gradient ascent schema is applied for locally area coverage optimal configuration.

The concept of network dynamics is proposed, the associated potential functions that encode the operational goals and environment are defined, and the laws of motion which are formulated using the steepest descent method in optimization are applied for managing mobility of mobile sensor network toward a better sensing coverage [58]. Based on the network dynamics model, a parallel and distributed algorithm (Parallel and Distributed Network Dynamics) that runs on each sensor node to guide its movement is devised. Sensor nodes are turned into autonomous entities that are capable of adjusting their locations according to the operational goals and environmental changes.

Two bidding protocols are designed to guide the movement of mobile sensors in sensor networks composed of a mixture of mobile and static sensors in which mobile sensors can move from dense areas to sparse areas to improve the overall coverage [59]. In the protocols, static sensors detect coverage holes locally by using Voronoi diagrams, and bid for mobile sensors based on the size of the detected hole. Mobile sensors choose coverage holes to heal based on the bid. This algorithm can provide suitable tradeoff between coverage and sensor cost.

Hybrid sensor networks which comprise of mobile and static sensor nodes for the purpose of collaboratively performing tasks like sensing a phenomenon or monitoring a region is studied [60]. Mobile sensor nodes are guided by the static sensor nodes to the phenomenon. Navigation is accomplished using the concepts of credit based field setup and navigation force from static sensor nodes. The approach does not require any prior maps of environment.

Yang et al. use a grid-based network structure to detect low density areas, and then maximize sensing coverage through balancing sensor distribution with movement-assisted sensor deployment [61]. The Scan-based Movement-Assisted sensoR deploymenT (SMART) algorithm, which is a hybrid approach of the local and global methods, and several variations of it that use scan and dimension exchange to achieve a balanced state are presented.

The coverage problem for hybrid networks which comprise both static and mobile sensors is considered [62]. The mobile sensors only have limited mobility. They can move only over a short distance. The authors investigate the distance that a mobile sensor will have to move in both all-mobile sensor networks and hybrid sensor networks. Their study formalizes the tradeoff that exists between an all-static network and a network with mobile sensors. Their results prove that from a scalability point of view, introducing mobility has significant advantages in providing coverage.

Chellappan et al. also study the deployment of sensor networks with limited mobility sensors, where the maximum distance that sensors are capable of moving to is limited [63]. First the field is clustered into multiple regions, the regions are assigned weights corresponding to the number of sensors needed. The deployment is to determine a movement plan for the sensors to minimize the variance in number of sensors among the regions, and simultaneously minimize the sensor movements. During sensor movement across the regions, larger weight regions are given higher priority compared to smaller weight regions, while simultaneously ensuring minimum number of sensor movements. The authors also study the deployment of mobile sensor networks, the mobility in the sensors is restricted to a flip, where the distance of the flip is bounded [64]. The deployment is to maximize the sensor network coverage and minimize the number of flips. Their solution optimizes both the coverage and the number of flips. The sensitivity of coverage and the number of flips to flip distance under different initial deployment distributions of sensors are also studied.

Bisnik et al. analyze how the quality of coverage scales with velocity, path, and number of mobile senors [65].

Dynamic Coverage Maintenance (DCM) schemes which exploit the limited mobility of the sensor nodes are proposed for coverage loss problem caused by early failure of sensor nodes [66]. DCM schemes can be executed on individual sensor nodes having a knowledge of only their local neighborhood topology. Four algorithms are proposed to decide which neighbors to migrate, and to what distance, such that the energy expended is minimized and the coverage obtained for a given number of live nodes is maximized. The decision and movement is completely autonomous in the network, and involves movement of one-hop neighbors of a dead sensor node.

Enhanced differentiated surveillance (EDS) is proposed to maintain the required coverage for sensor networks by establishing working schedules of sensors for the purpose of energy saving [67]. Every sensor in a sensor network is allowed to establish its working schedule in a distributive manner based on random reference times generated through integer hashing and a proposed coverage measurement rule. The required coverage is continuously guaranteed when every sensor senses following its own working schedule. EDS can be applied to sensors with different sensing ranges and random mobile sensor networks, where sensors randomly roam and cannot control their movements. The advantages of EDS lie in minimum communication overhead, fast convergence, load balancing, and high battery efficiency.

Many existing deployment schemes largely oversimplify the conditions for network connectivity. Two sensor deployment schemes, Connectivity-Preserved Virtual Force (CPVF) scheme and Floor-based scheme, are presented to maximize sensing coverage and also guarantee connectivity for a network with arbitrary sensor communication/sensing ranges or node densities, at the cost of a small moving distance [68]. The schemes do not need any knowledge of the field layout, which can be irregular and have obstacles/holes of arbitrary shape.

The stochastic model assumed to govern the mobility of nodes in a mobile ad hoc network has been shown to significantly affect the network's coverage, maximum throughput, and achievable throughput-delay trade-offs. Several mobility models, including the random walk, random waypoint, Manhattan models and proposed correlated random walks are compared [69].

A distributed energy optimization sensor deployment method for heterogeneous sensor network is proposed

[70]. Sensor nodes are clustered by maximum entropy clustering. The sensing field is divided for parallel sensor deployment optimization. For each cluster, the coverage and energy metrics are calculated respectively. Cluster heads perform parallel particle swarm optimization to maximize the coverage metric and minimize the energy metric.

B. Dynamic area coverage with controllable mobility

Liu et al. study the coverage of mobile sensor network from a very different perspective [71]. Instead of trying to achieve an improved stationary network configuration as the end result of sensor movement, the authors focus on the dynamic aspects of coverage capabilities resulted from the continuous movement of the sensors. The dynamic coverage of mobile sensor network is characterized as area coverage at specific time instants and during a time interval, and the detection time of a randomly located target. These coverage measures depend on the process of sensor movement and are unique attributes of mobile sensor networks. Their research results show that sensor mobility, random mobility model for sensors, can be exploited to compensate for the lack of sensors and improve network coverage.

Hussein et al. formulate the dynamic coverage problem in a mathematically precise problem statement [72]. Its coverage goal is to cover a given search domain using multiple mobile sensors such that each point is surveyed until a certain preset level is achieved. A control law is modified to guarantee that a partially connected fleet also attains the coverage goal. A collision avoidance component is added to the controller to guarantee that the agents do not collide.

Cheng et al. propose a gradient-based motion control strategy for optimizing the target sensing quality while guaranteeing the required coverage of the field of interest [73].

IV. Simultaneous Localization, Mapping and Exploration of Multi-robot Systems

Autonomous environment exploration, mapping and concurrent localization in the map is a key mission of mobile sensor network for practical applications in real unknown environments, for example, surveillance, reconnaissance, planetary exploration and rescue missions. Networked robot teams provide higher efficiency and higher accuracy for simultaneous localization and mapping (SLAM) and exploration.

Multi-robot SLAM has mostly been addressed in data fusion aspect characterized by two major sources of uncertainty due to the noise in sensing and in motion without considering controllable mobility [74]. That is, mobile robots randomly move in the environments. Extended Kalman filter and particle filter approaches have been successfully implemented for data fusion of multi-robots SLAM [75]. Map merging that partial maps have merged into a single environment map is also studied [76]. Classical SLAM approaches are passive in the sense that they only process the perceived sensor data and do not actively control the motion of the mobile robots for the purpose of SLAM.

Active SLAM, planning motion actions for SLAM, has been studied for single robot [77]–[83]. The probabilistic measure of 'entropy' as a information-based measure of the certainty in the map and vehicle locations has been used as a utility function for planning the vehicle trajectory. Observability analysis of SLAM presents that the unobservable states dependent on vehicle maneuvers [82]. Bayesian optimization method dynamically trades off exploration (minimizing uncertainty in unknown parts of the space) and exploitation (capitalizing on the current best solution) [83]. A method for evaluating the quality of actions for a single camera while mapping unknown indoor environments is presented [84]. They study controllable mobility for bearing-only single-camera SLAM.

Active SLAM trajectory control strategies for multiple cooperating UAVs is developed [85]. Each UAVs shares map information over a data fusion network. Multi-vehicle active SLAM control architectures are proposed that actively plan the trajectories and motions of each vehicle in the team based on maximizing information in the localization and mapping estimates. A coordinated, decentralized architecture, where UAVs make their own control decisions based on common shared map information, is proposed. The different architectures involve varying degrees of complexity and optimality through differing communications and computational requirements.

Exploration strategies often try to cover unknown terrain as fast as possible and avoid repeated visits to known areas. However the robot typically needs to revisit places to localize itself again. An integrated approach that combines autonomous exploration with simultaneous localization and mapping is presented [86]. With a grid-based version of the FastSLAM algorithm, actions to actively close loops during exploration are considered at each point in time. By re-entering already visited areas, the robot reduces its localization error and in this way learns more accurate maps.

A multi-robot system can be highly beneficial for exploration. The overall performance can be much faster and more robust with controllable mobility. The goal of multi-robot environment exploration is to choose appropriate target points for the individual robots so that they simultaneously explore different regions of the environment. An approach which simultaneously takes into account the cost of reaching a target point and its utility is presented to coordinate multiple robots [87]. Whenever a target point is assigned to a specific robot, the utility of the unexplored area visible from this target position is reduced. Different target locations are assigned to the individual robots. The effective coordination cannot be achieved if the robots do not share a common map. Thus, their relative locations' estimation is very important to estimate whether or not the partial maps of two robots overlap. In order to overcome the risk of false-positive matches, the robots communicate with each other actively verify location hypotheses using a rendezvous strategy [88]. If the robots meet at the meeting point, they know their relative locations and can combine their data into a shared map. The high accuracy and robustness can be achieved at the cost of low efficiency.

Communicative exploration approach to multi-robot exploration is presented that takes the constraints of wireless networking, namely the limited range of the transceivers, into account [89]. A simple utility function is used to guide the movements of the robots. The algorithm proceeds in time steps where in each step a random population of so-called configuration changes is generated. The configuration changes represent possible movements of the different robots. The best configuration change according to the utility function is selected in each time step and executed. Their research shows that the robots can get stuck in deadlock situations, which form a kind of local optima in the utility. Roles are used as a remedy for this. They select one robot as a meeting point and the others move there. They only traverse the already known and mapped regions of the environment. When they are close to the meeting point and in communication range with each other, the normal exploration behavior proceeds. However, the efficiency decreases and energy consumes due to the robots traverse the already mapped regions for the deadlock recovery.

A strategy to select optimal motions of multi robot systems equipped with cameras for improving the observation of the environment is studied [90]. A solution designed for omnidirectional cameras is presented. The key idea is the selection of a finite set of candidate next positions for every robot within their local landmark-based stochastic maps. In this way, the cost function measuring the perception improvement when a robot moves to a new position can be easily evaluated on the finite set of candidate positions. Then, the robots in the team can coordinate based on these small pieces of information. The proposed strategy is designed to be integrated with a map merging algorithm where robots fuse their maps to get a more precise knowledge of the environment. The interest of the proposed strategy for uncertainty reduction is that it is suitable for visual sensing, allows an efficient information exchange, presents a low computational cost and makes the robot coordination easier.

A hybrid reactive/deliberative approach to the multi-robot SPLAM problem is presented [91]. The design of the reactive and deliberative processes is exclusively oriented to the exploration having both the same importance level. The approach is based on the concepts of expected safe zone and gateway cell. The reactive exploration of the expected safe zone of the robot by means of basic behaviors avoids the presence of local minima. Simultaneously, a planner builds up a decision tree to decide between exploring the current expected safe zone or changing to other zone by traveling to gateway cell. The model takes into account the degree of localization of the robots to return to previously explored areas when it is necessary to recover the certainty in the position of the robots.

V. Target Detection, Localization and Tracking with Mobile Sensor Network

Target detection, localization and tracking has recently received significant interest because of its importance in a variety of applications such as environmental monitoring, surveillance and military applications. Its goal is to determine the number, position, and movement of targets. Many research works consider the motion control of autonomous robots for searching/tracking targets [92]–[96]. However, controllable mobility in mobile sensor network for target detection and tracking poses several new challenges that have not been addressed in the existing robotic motion planning literature, which include limited mobility of sensors, resources constraints, and stringent quality-of-service requirements such as low false alarm rate, high detection probability and bounded detection delay [97].

On the other hand, collaborative target detection and tracking with stationary wireless sensor networks has been extensively studied [98]–[101]. Due to unpredictable spatiotemporal distributions physical phenomena and dynamic changes of network conditions or physical environments, static sensor network even if a large network deployment cannot achieve satisfactory sensing performance.

Mobile sensor nodes can dynamically reconfigure the sensor network capability to cope with the unpredictability and variability of physical reality and improve the robustness of sensor networks.

A. *Active target estimation with range-only measurements*

Active target estimation is one of the basic problem for mobile sensor network: where the sensors should move to attain the best estimates of the targets meanwhile guaranteeing the optimal consumption of communication bandwidth, CPU time, and power consumption. A team of indoor robots equipped with laser range finders are coordinately controlled to maximize the information measures for multi-feature localization [102].

B. *Active target estimation with bearing-only measurement*

A team of mobile agents equipped with cameras are actively controlled to optimize the quality of the targets' estimates that reflects the expected value of assuming a particular formation prior to the data fusion phase [103]. The optimization is implemented centrally.

Information measures are used to communicate state estimates in mobile sensor network [104].The information measures are maximized to implemented the coordinated control of robot sensors. The approach inherits many benefits of decentralized data fusion including scalability, robustness and interoperability among heterogeneous systems. It is applied to a practical bearing-only multi-feature localization problem.

A solution to the optimal trajectory planning problem in target localization for multiple heterogeneous robots with bearing-only sensors is provided [105]. Its objective is to find robot trajectories that maximize the accuracy of the locations of the targets at a prescribed terminal time. Nonlinear Model Predictive Control (MPC) is used for the optimization problem.

Hoffmann et al. develops a set of methods enabling an information-theoretic distributed control architecture based on particle filters to quickly localize a target with bearing-only measurements by a mobile sensor network, permitting the use of nonlinear and non-Gaussian sensor models [106]. This method exploits the structure of the probability distributions of the target state and of the sensor measurements to compute the control inputs to the mobile sensors leading to future observations that minimize, in expectation, the future uncertainty. The mutual information is computed using a particle set representation of the posterior distribution. Single-node and pairwise-node approximation schemes for mutual information in a large mobile sensor network are presented. The methods can guarantee analytically bounded error, the approach scalable to increasing network sizes. The authors develop the above methods to make the information theoretic ideas tractable and scalable for real-time control of a mobile sensor network for general sensors (including bearings-only sensing, range-only sensing, and magnetic field sensing), dynamics (the dynamics of actual vehicles), and available prior knowledge (search regions can be complicated to represent) [107].

C. Active target estimation with range-bearing measurement

Gradient-searching-based decentralized algorithm is presented for decentralized control mobile nodes mounted with sonar to estimate the state of a dynamic target [108]. The cost function for optimization is the determinant of the error covariance matrix. The decentralized control law is based on the gradient of the cost function with respect to each of the sensor's coordinates. Stroupe and Balch consider to minimize the target's location uncertainty using distance and bearing measurements [109]. The objective function is the determinant of the target position estimates' covariance matrix. A greedy search is performed over the discrete set of candidate headings on each sensor node separately. In both of their research, each sensor node optimizes its own next move with the assumption that other nodes remain at their current locations.

D. Active target tracking with range-only measurement

A general theme in probabilistic tracking control is the balance between computational efficiency and the need to model a non-Gaussian, multi-modal target estimate distribution because the fact that the sensor platform is kinematically constrained and the target motion is either very agile or uncertain, the target may be lost.

The problem of optimal trajectory generation for a team of mobile sensors tracking a moving target using distance-only measurements studied [110]. The constraints are imposed on the speed of the sensors. Two algorithms, modified Gauss-Seidel relaxation and linear programming (LP) relaxation, are proposed for determining the set of feasible locations that each sensor should move to in order to collect the most informative measurements, distance measurements that minimize the uncertainty about the position of the target. These algorithms can be applied for any process model that is employed for describing the motion of the target. And the computational complexity is linear in the number of sensors. The performance attained with the proposed methods is significantly better than that of a random, toward the target, motion strategy.

For a target-tracking application with range sensors, the determinant of the Fisher Information Matrix is investigated for 'range-measurement' models [111]. The FIM determinant, aggregate cost function encoding a 'sensitivity performance measure' plays the role of an object function. Decentralized control laws for the optimal positioning of sensor networks that track a target is presented.

Makarenko and Durrant-Whyte investigate the design of distributed motion coordination algorithms that increase the information gathered by a network in static and dynamic target-tracking scenarios [112]. An aggregate cost function encoding a 'sensitivity performance measure' is defined. The closed-form expressions for the determinant of the Fisher Information Matrix for 'range-measurement' models are presented. This determinant plays the role of an objective function. On the objective function, a decentralized control laws for the optimal positioning of sensor networks that tracks a target is presented.

E. Active target tracking with range-bearing measurement

A simple gradient-searching-based decentralized algorithm is extended for the task of tracking multiple targets with the assumption that sensors is capable of taking measurements of all targets simultaneously [108]. Based on this method, the authors study a cost function that measures the overall quality of sensing for localization and tracking dynamic targets. The role of imperfect communication between sensor agents is investigated. The trade-offs in performance between sensing and communication is examined [113].

The problem of multiple mobile sensor agents tracking the position of one or more moving targets is studied [114]. Each agent maintains a target estimation, and each agent moves so as to maximize the expected information from its sensor, relative to the current uncertainty in the estimate. In their research, each agent need only communicate with one-hop neighbors in a communication network, resulting in a fully distributed and scalable algorithm.

A flocking-based mobility model is used for moving target tracking with mobile sensor network in dynamic communication topology [115]. The target's state (position, velocity, and acceleration) is estimated with a modified distributed Kalman filter by using distance and bearing measurements to a target that moves in 2D with constant velocity driven by zero-mean Gaussian noise under the assumption that the position and orientation of each sensor are known with high accuracy within the global frame of reference. The sensor nodes try to move to the target while avoiding collisions. As the agents flock towards the target, the information value of their measurements improves in time. The positioning information from previous time-steps is not considered.

The problem of determining optimal trajectories for a team of heterogeneous mobile sensors that track a moving target using distance and bearing measurements is addressed [116]. The optimality criterion is to minimize the trace of the target's position covariance matrix. The authors account for the existence of prior information and explicitly consider limits on the robots' speed and impose constraints on the minimum distance at which the robots are allowed to approach the target. An iterative algorithm, Gauss-Seidel-Relaxation (GSR) is proposed for determining the set of feasible locations that each sensor should move to in order to minimize the uncertainty about the position of the target. Their research result shows that the performance of the GSR, whose computational complexity is linear in the number of sensors, is indistinguishable of that of a grid-based exhaustive search, with cost exponential in the number of sensors, and significantly better than that of a random, towards the target, motion strategy.

Because the energy required for locomotion energy is much higher than that for sensing and communication, it is not always favorable for sensor nodes to move [117]. Zou and Chakrabarty propose that node considers movement only if it detects a target [118]. The authors consider not only the positive consequences but also the negative consequences of node movement,e.g., additional energy consumption, connectivity loss, and coverage loss. A mobility management framework that unifies tracking quality, sensing coverage, network connectivity, and energy consumption is introduced for the specific objective of target tracking. Their research makes many assumptions that both sensor nodes and the target are moving at constant speeds, and all nodes have the same number of candidate locations in gridded sensing region.

Baumgartner et al. study the optimal control of an underwater sensor network for cooperative target tracking [119]. An integral objective function representing the quality of service of a sensor network performing cooperative track detection over time is derived using a geometric transversal approach. Each sensor-equipped vehicle is modeled as a bounded subset of a Euclidian space, representing the sensor's field of view (FOV), which moves according to underwater vehicle dynamics. By this approach, the problem of generating optimal sensors' trajectories is formulated as an optimal control problem in computational geometry.

F. Target detection with mobile sensor network

Wireless sensor networks deployed for mission-critical applications face the fundamental challenge of meeting stringent spatiotemporal performance requirements using nodes with limited sensing capacity. Although advance network planning and dense node deployment may initially achieve the required performance, they often fail to adapt to the unpredictability and variability of physical reality. Mobile sensors can be exploited to address limitations of static WSNs for target detection.

The problem of detecting the presence/absence of a target using mobile sensor network is investigated [120]. It presents an analytic method to evaluate the detection latency based on a collaborative sensing approach using nodes with uncoordinated mobility. With the analytic model, the tradeoff between number of nodes and detection latency in a mobile sensor network is analyzed. Their research results show that if the target is present at the worst possible location in a given deployment, then detection latency of mobile sensor networks is considerably less as compared to that of stationary networks with the same number of nodes. The research is based on random mobility model and does not address the issue of actively controlling the movement of sensors.

The stochastic event capture problem, the events of interest arrive at certain points in the sensor field and disappear according to known arrival and departure time distribution, is considered [65]. An event is said to be captured if it is sensed by one of the mobile sensors before it fades away. The authors characterize cases where the deployment of mobile sensors has no advantage over static sensors, and find the optimal velocity pattern that a mobile sensor should adopt. For sensors with fixed speed, the minimum number of sensors required to satisfy a bound on the event loss possibility is given.

Exposure, which measures how the region is covered by the sensor network, one of the fundamental issues in target detection problem, is defined as the least probability of detecting a target over all possible target maneuvers for some time and evaluated in the context of mobile sensor network with the presence of obstacles and noise [121]. Detection is conducted without presuming the target's activities and moving directions. The research shows that exposure can be improved by patrolling static routes with mobile sensors.

Two data fusion based detection models that enable static and mobile sensors to effectively collaborate in target detection are proposed. A decision-fusion-based detection model in which each mobile sensor makes its own detection decision and locally controls its movement is presented [122]. The mobile sensor is required to be able to locally detect targets and adaptively control their movement. Reactive mobility is exploited to improve the target detection performance of wireless sensor network. Sparsely deployed mobile sensors collaborate with static sensors and move in a reactive manner to achieve required detection performance. Specifically, mobile sensors remain stationary and are directed to move toward a possible target only when a detection consensus is reached by a group of sensors. The accuracy of final detection result is then improved as the measurements of mobile sensors have higher Signal-to-Noise Ratios after the movement. A sensor movement scheduling algorithm that achieves near-optimal system detection performance under a given detection delay bound.

The authors also present a value-fusion-centric target detection model for effective collaboration between static and mobile sensors [97]. Each mobile sensor in a detection process is only required to move a certain distance and send its measurements to its cluster head which is the closest to the surveillance location. An optimal sensor movement scheduling algorithm is developed to minimize the total moving distance of sensors while achieving a set of spatiotemporal performance requirements including high detection probability, low system false alarm rate, and bounded detection delay. The multitarget detection problem is studied. Their research assumes that the clocks of all sensors are synchronized and each mobile node knows its own location and can orient its movement in a given direction. Their work considers the power consumption of locomotion and the mobile sensors move reactively only when a coarse detection consensus is reached and the power consumption of locomotion is minimized. Their work focuses on online sensor collaboration and movement scheduling strategies that are used after the appearance of targets.

It is important to detect intruders in the field of interest as quickly as possible, especially when the intruders are hostile. The detection time of an intruder is defined to be the time elapsed before the intruder is first detected [71]. Intruders that will never be detected in a stationary sensor network can be detected by moving sensors. The distribution of the detection time for a randomly located stationary intruder is obtained. A game theoretic approach is used to detect mobile intruders. The best worst-case performance of a mobile sensor network in terms of the intruder detection time is studied.

The impact of mobile node density on several detection performance measures for stationary target detection by a hybrid sensor network consisting of both static and mobile nodes is investigated [123]. Hybrid sensor networks are becoming attractive with the recent advances in mobile sensor nodes. Adding a large number of mobile nodes to a sensor network for continuous coverage improvement might be expensive due to mobile node's higher energy consumptions. The trade-off between the density of mobile nodes and the network performance in a hybrid sensor network with respect to several performance measures of interest, when mobile nodes perform random mobility, is investigated. Detection probability, detection latency and mean first contact distance are used to evaluate the trade-off between the fraction of mobile nodes and these performance measures.

Stochastic model assumed to govern the mobility of nodes in a mobile ad hoc network significantly affects the event detection time [69]. Their research result can provide guidelines on how many mobile sensor nodes should be deployed to achieve the required event detection rates, given the mobility characteristic of these mobile nodes.

VI. Perimeter Detection and Tracking

A perimeter, an area enclosing some type of substance, may be static or dynamic. Perimeter detection and tracking has a wide range of applications: detection and tracking radiation/chemical spills, tracking oil spills in ocean, detection of algae bloom, and tracking forest fires etc. In perimeter detection and tracking tasks, mobile sensor network locates, surrounds and tracks a substance while dynamically reconfiguring as environment or network itself changing. Perimeter detection and tracking using mobile sensor network has the advantage of operating in a wide variety of situations like changing perimeters (spill monitoring, forest fire surveillance) or large perimeters (border patrol). Most of the approaches to track perimeters fall into two main groups: gradient-free approaches and gradient-based approaches.

A. Gradient-based approaches for perimeter detection and tracking

Marthaler et al design a centralized collective motion algorithm based on the 'snake algorithm' in image processing to detect and track algae blooms, where each agent needs to measure the concentration gradient [124].

Clark and Fierro use random coverage controller, potential field controller and a bang-bang angular velocity controller to detect and track the dynamic perimeter of oil spills [125]. Their work did not analyze the efficiency and the convergence of the algorithms and did not consider the limited communication range problem.

Dantu and Sukhatme consider a heterogeneous sensor network for detecting and tracking a specified level set of a scalar field (a contour) on a plane [126]. A network of static sensor nodes with limited communication and processing are deployed in a planar environment along with a mobile node which can both sense and move. As the mobile node moves through the environment, it computes the local spatial gradient of the field by communicating with its immediate neighbors in the static sensor network. The mobile node performs gradient descent on the scalar field till it arrives at a location on the desired contour.

Susca et al. [127] addresses the problem of boundary estimation and tracking by means of robotic sensors. Their research assumes that each mobile agent is equipped with 1) a sensor that provides only local information about the tangent and curvature of the boundary rather than the general gradient information, and 2) a communication device that enables information exchanges between clockwise and counterclockwise neighbors along the boundary. The method appropriates a changing border with a set of interpolation points . The mobile agents move counterclockwise along the time-varying boundary with varying speed. It locally optimizes its position along the updated estimate of the curve of boundary. Every agent estimates the arc length distance between itself and its immediate clockwise and counterclockwise neighbors and uses this information to speed up or slow down. As the team agents traverse the perimeter, they update the points that describe the perimeter to best fit a polygon to the shape of the perimeter. With the help of mobility, only very limited mobile sensors are needed for the varying boundary estimation and tracking.

B. Gradient-free approaches for perimeter detection and tracking

The gradient-free approaches for perimeter detection and tracking use less information than the gradient-based approaches. The direction of movement of mobile sensors at the next step is not completely obvious. The gradient-free approaches depend on only sensor density observations about the surrounding. The main work in on how to deal with measurement noises.

A simple algorithm is proposed for multiple UUVs monitoring an underwater perimeter that only requires scalar concentration measurements [128]. Each individual vehicle moves either clockwise or counterclockwise around a nearby circle with a prescribed radius and center. The method has been tested on Caltech's land testbed with second order vehicles without sensor noise (and with only simulated sensors) [129].

Jin and Bertozzi develop a framework for environmental boundary tracking and estimation by considering the boundary as hidden Markov model (HMM) with separated density observations collected from multiple sensing vehicles. Page's cumulative sum algorithm (CUSUM) is used for change-point detection [130]. Joshi and Bertozzi implement the above algorithm on a cooperative testbed for environmental boundary tracking and estimation using only localized noisy sensors [131]. A geometric, biologically inspired motion control algorithm allows individual vehicles to track and follow the environmental boundary without external positioning information. Relative positioning between vehicles allows vehicles to maintain a convoy while tracking the boundary.

Casbeer et al. explore the feasibility of using multiple low-altitude, short endurance unmanned air vehicles to cooperatively monitor and track the propagation of large forest fires [132]. A real-time algorithm is described for tracking the perimeter of fires with an on-board infrared sensor. The UAVs are assumed to have limited communication and sensing range. Each UAV uploads data to the base station and it must periodically return to the base station for refueling. The base station deploys multiple UAVs to monitor the propagation of the fire with a cooperative surveillance strategy that minimizes the latency associated with fire perimeter measurements delivered to the base station by minimizing the time of flight between points on the perimeter and the base station, and by maximizing the frequency of measurement updates delivered to the base station.

Kingston et al. [133] presents a fully decentralized algorithm for perimeter surveillance with taking into account of communication range limitations and allowing for changing perimeters. The method can guarantee convergence in finite time. By sharing information regarding the perimeter length and number of team members, each agent obtains a consistent set of coordination variables that allows the decentralized algorithm to operate effectively. The method has the ability to monitor changing perimeters, account for dynamic insertion and deletion of team members, and the ability to operate with a small communication range in a decentralized manner. The algorithm is limited to constant velocity vehicles that travel along the border and is not as efficient in the transient period as compared with a centralized algorithm.

Stranders et al. use autonomous unmanned vehicles which have ability to situational awareness to patrol environments [134], especially for environments that are subject to continuous change. Based on a non-myopic divide and conquer algorithm for computing near-optimal patrols for single mobile sensor, an algorithm for computing near-optimal patrols for multiple agents by iteratively computing single-agent policies is presented.

VII. Spatio-temporal Dynamic Fields Modeling in Large Environment

Mobile sensor networks have potential for spatio-temporal dynamic scalar and vector fields modeling in large environment, such as environmental temperature or density of adversarial agents, as a function of the spatial location or time sequence. Mobility of the agents can be applied to improve the estimate of the modeled variable.

The problem of modeling a scalar field with estimation-and-control approach is formulated [135]. A measure of the model quality is defined and a gradient control law is used to move the agents to collect sensor data that improves the quality of the model. The method is implemented in decentralized case where there is no particular structure on the communication network, agents can be added or subtracted at any time.

Motivated by the Autonomous Ocean Sampling Network-II(AOSN-II) and the Adaptive Sampling and Prediction (ASAP) projects, Leonard et al. apply a fleet of self-directed underwater gliders to sample dynamic ocean variables for autonomous ocean observing and prediction in costal ocean modeling [136]. A framework using Virtual Bodies and Artificial Potential (VBAP) is introduced [137]. A performance metric, used to derive the optimal paths for the network of mobile sensors, defines the optimal data set as one which minimizes error in a model estimate of the sampled field. Feedback control laws are presented that stably coordinate sensors on structured tracks that have been optimized over a minimal set of parameters [136].

Four robots are used to compose a formation so that the gradient at the formation center can be measured in a large scale density field [138].

Path planning and trajectory design of autonomous underwater vehicles (AUVs) for oceanographic modeling is also addressed in [139]. The paths of AUVs are determined to track evolving features of interest in the ocean by considering the output of predictive ocean models.

Choi and How extend the active sensing problem [140]. Their research investigates continuous trajectory planning of mobile sensors to minimize the uncertainty in some verification variables in the future. Filter form and smoother form are compared for computing the mutual information. A gradient-ascent steering law based on the concept of information potential field is presented as a computationally efficient suboptimal strategy. The strategies are implemented with a simplified weather forecasting example.

VIII. Conclusions

Recent literature shows that researchers have focused their attention on use controllable mobility to address various wireless sensor network applications such as localization, coverage, mapping, exploration, target detection and tracking, perimeter detection and tracking, and spatio-temporal dynamic fields modeling in large environment. Different trajectory planning algorithms are studied for mobile sensor network aiming at different tasks. In spite of a multitude of successful researches on controllable mobility for active sensing of mobile sensor network, the main concern is that the most of the these algorithms are still in development stage. Most of the current trajectory planning for active sensing are heuristic lacking of substantial theoretical analysis. Future research is likely to focus on developing well-founded analytical trajectory planning approach for active sensing of mobile sensor network. The goal for the future of controllable mobility in mobile sensor network is to improve already existing solutions, refine them and develop well-founded practical trajectory planning algorithms.

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