Considerations on Coverage and Navigation in Wireless Mobile Sensor Network

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Abstract:

In wireless mobile sensor networks, periodic calculation of coverage is very important, since mobile sensors can be moved adequately to current needs, thus increasing the coverage. Those moves require the execution of navigation tasks. Global network central algorithms for those tasks are very costly regarding energy consumption and computational resources. Considerations presented herein pertain to the best algorithms for a network of numerous small mobile sensor nodes used for monitoring of large terrains. Localized algorithms suggested in this paper help calculate the coverage on-line and locally with the involvement of neighboring nodes only. Furthermore, localized collaborative navigation is presented. It enables yielding position estimation with no GPS use and ensures improvement rather than deterioration over time. It uses multi-sensor fusion algorithms based on optimization and a distributed iterative extended Kalman Filter.

Keywords: *wireless, mobile sensor network, coverage, navigation.*

1. Introduction

There are two major problems regarding wireless mobile sensor networks, i.e. whether a network has adequate coverage of monitoring area and whether a network is able to rearrange sensor-nodes to fulfill the specific requirements of coverage. The ability to self-deploy and self-configure is of critical importance for mobile sensor networks because of the unattended nature of intended applications. The network should be able to dynamically adapt its topology to meet application-specific requirements of coverage and connectivity. In static networks, topology control is achieved by controlling the transmission power or sleep/wake schedules of densely deployed nodes. In contrast, mobile sensor networks can exploit control over node positions to affect network topology thus eliminating the need for over-deployment and increasing the net area sensed. A key challenge posed by this objective is the typically global nature of the desired network properties, one of which is coverage of a network.

A wireless sensor network is a collection of sensors that offer the ability to communicate with one another and the ability to sense the environment around them, but have limited computational and battery capacity, e.g. solar-powered autonomous robots. These considerations concern the best algorithms for a network of numerous small mobile sensor nodes used for monitoring of large terrains, including those used in safety applications. This paper attempts to select the best solution to how a wireless mobile sensor network could take advantage of its mobility to improve its coverage by self-deployment of sensors consuming as little power as possible. Power consumption is of critical importance in such networks. Topology control algorithms that reduce energy consumption have been an area of thorough research and numerous works, many of which are presented in [1]. Our paper describes selected techniques for evaluation of both coverage and localization of nodes, focusing on those presenting a distributed method and requiring as low energy consumption and as little computation resources as possible. The remaining sections are organized as follows: Section 2 provides the theoretical framework of coverage, Section 3 describes evaluation of sensor field exposure, Section 4 contains a short review of existing works concerning algorithms for coverage calculation, Section 5 presents the distributed algorithm for minimal exposure path evaluation, Section 6 pertains to navigation problems in mobile sensor network, Section 7 presents distribution multi-sensor fusion algorithm for navigation and Section 8 presents performance analysis of location estimates. The last section provides some conclusions and gives suggestions for future work.

2. Calculation of coverage

One of the fundamental problems regarding sensor networks is the calculation of coverage. Exposure is directly related to coverage in that it is a measure of how well an object, moving on an arbitrary path, can be observed by the sensor network over a period of time. The minimal exposure path is a path between two given points such that the total exposure acquired from the sensors by traversing the path is minimized [2]. The path provides information about the worst-case exposure-based coverage in the sensor network. Exposure can be defined as an integral of a sensing function that generally depends on the distance between sensors on a path from a starting point *pS* and a destination point *pD*. The specific sensing function parameters depend on the nature of the sensor device and usually have the form d^{-K}, with K typically ranging from 1 to 4.

Generally speaking, sensors have broadly diversified theoretical and physical characteristics. Most sensor models share two facets:

- sensing ability diminishes as distance increases;
- sensing ability improves as the sensing time (exposure) increases (due to noise effects).

With this in mind, for a sensor *s*, the general sensing model *S* at an arbitrary point *p* can be expressed as follows:

$$S(s,p) = \frac{\lambda}{[d(s,p)]^K} \quad (1)$$

where *d(s,p)* is the Euclidean distance between the sensor *s* and the point *p*, and positive constants λ and *K* are sensor technology-dependent parameters.

3. Sensor Field Intensity and Exposure

In order to introduce the notion of exposure in sensor fields, the Sensor Field Intensity for a given point *p* in the sensor field *F* should be defined. Sensor field intensity can be defined in several ways. Two models are presented for the sensor field intensity: All-Sensor Field Intensity and Closest-Sensor Field Intensity.

Exposure for an object *O* in the sensor field during the interval $[t_1, t_2]$ along the path *p(t)* is defined [3] as:

$$E(p(t), t_1, t_2) = \int_{t_1}^{t_2} I(F, p(t)) \left| \frac{dp(t)}{dt} \right| dt \quad (2)$$

where:

$$\left| \frac{dp(t)}{dt} \right| = \sqrt{\left(\frac{dx(t)}{dt}\right)^2 + \left(\frac{dy(t)}{dt}\right)^2}$$

All-Sensor Field Intensity for a point *p* in the field *F* is defined as the effective sensing measurements at point *p* from all sensors in *F*. Assuming there are n active sensors, $s_1, s_2, \ldots s_n$, each contributing with the distance-dependent sensing the function can be expressed as:

$$I_A(F, p) = \sum_{1}^{n} S(s_i, p) \quad (3)$$

Centralized method algorithm requires sensor nodes not only to perform the exposure calculation and shortest-path searching in the sensor network, but also to know the topography of the network. Both functionalities, particularly discovering the network topography, may require extensive computation resources and energy consumption. Communication, required to discover the network topography, is the major energy consumer in wireless sensor networks. Therefore, it is important that a localized minimal exposure path algorithm is developed so that sensors can estimate the network's minimal exposure path without having to know the entire network's topography. In such a localized algorithm, the number of messages sent across the network and the computation performed at each node should be kept at the minimum level.

4. Algorithms for coverage evaluation

Most research conducted so far has focused on reducing the design and maintenance (including deployment) costs or increasing the sensor network's reliability and extending its lifetime. However, another crucial problem is to determine how successfully the sensor network monitors the designated area. This is one of the most important criteria for evaluating the sensor network's effectiveness [4]. Another problem is the navigation of mobile nodes in order to improve coverage of the network. We review several techniques of coverage estimation and a few techniques for localization and navigation of mobile sensor-nodes in order to move it to improve the coverage of the sensor network. Coverage in a mobile sensor network can be evaluated as optimization problem for best case or worst-case coverage. The best-case coverage involves two approaches: maximum exposure path and maximum support path. The worst-case coverage has another two: maximum breach path and minimum exposure path [5]. For safety applications, the latter two approaches are chosen. Maximum breach path is not a unique one, since it finds a path such that the exposure at any given time does not exceed a given value. Therefore, the minimum exposure path is chosen, since it attempts to minimize the exposure acquired throughout entire measured time interval. Determining such a path enables the user to change the current location of some nodes to increase the coverage. The authors of [6] suggest that the problem should be transformed to a discrete by generating *n* x *n* square grid and limit the existence of the minimal exposure path only along the edges and diagonals of each grid square. Each edge is assigned a weight calculated by special function using numerical integration. The solution produced by the algorithm approaches optimum at the cost of run-time and storage requirements. [7] discusses an algorithm for a network that initially deploys a fixed number of static and mobile nodes and then static nodes find the coverage holes and mobile nodes are relocated to the targeted localizations to increase coverage. In the next section, we present the distributed local algorithm, which do not present limitation of fixed number of nodes. The authors of [8] developed distributed algorithms for self-organizing sensor networks that respond to directing a target through a region and discussed self-organizing sensor networks capable of reacting to their environment and adapting to changes. It can also evaluate coverage of the network in a different way. They described an innovative application: using the sensor network to guide the movement of a user equipped with a sensor that can communicate with the network across the area of the network along a safest path. Safety is measured as the distance to the sensors that detect danger. The protocols for solving this problem implement a distributed repository of information that can be stored and retrieved efficiently when needed.

In [9], the author proposes a virtual force algorithm (VFA) as a sensor deployment strategy to enhance the coverage after initial random placement of sensors. For a given number of sensors, the VFA algorithm attempts to maximize the sensor field coverage. A discreet combination of attractive and repulsive forces is used to determine virtual motion paths and the rate of movement for the randomly placed sensors. Once the effective sensor positions are identified, a one-time movement with energy consideration incorporated is carried out and the sensors are redeployed to these positions.

5. Localized algorithm for minimum exposure calculation

The best solution for the objective set forth in these considerations is the localized algorithm for minimum exposure calculation proposed by Veltri and others [10]. It ensures low costs of communication and computation in the wireless sensor network without the necessity to determine the entire network's topography and does not require a fixed and limited number of nodes. In this algorithm, only neighboring nodes need to be updated with information and minimum path can be calculated on-line in an easy and efficient manner.

The following assumptions were made:

- sensor nodes do not possess the necessary knowledge to compute the shortest path locally and hence rely on forwarding messages to their neighbors using a shortest-path heuristics;
- a sensor node stores topological information it receives and forwards the topological information it knows;
- the Voronoi diagram-based minimum exposure path approximation algorithm is used to further reduce the computation (of exposure) at each sensor node.

To use the Voronoi diagram to estimate the minimum exposure path, grid points are placed along Voronoi edges, and grid points on the same Voronoi cell are fully connected (see Fig.1).

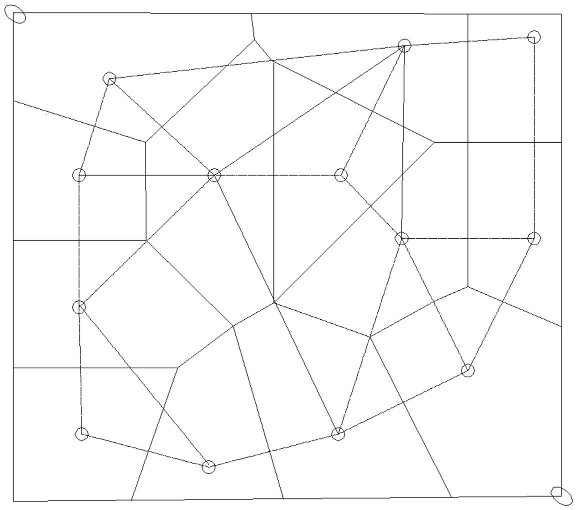

Fig. 1. Voronoi diagram for sensor network. Circles represent sensors, ellipses a starting point and a destination point.

The weight of an edge between two Voronoi grid points is the single-sensor optimal solution weight for the sensor corresponding to the Voronoi cell. However, this weight only applies if the shortest path lies entirely within the Voronoi cell. If the path strays beyond the Voronoi cell, a straight line is used to weight the edges. Furthermore, the single-sensor optimum solution is used to bound areas to search; if the single-sensor optimum solution between two points is larger than an already found estimated solution, those two points are not investigated during subsequent iterations of the localized algorithm.

Two types of messages, Forward messages and Search messages, are passed among sensors in the sensor network. Search message - the receiving node will search locally. Forward message - the receiving node will forward it to a neighboring sensor. To reduce the costs of communication and computation on the wireless sensor network, a heuristic method was applied to rapidly come to a solution that is hoped to be close to the best possible answer. A sensor node selects its neighbor node as the recipient of the message. It would pick the node that has potentially large number of distinct neighbors so that it can quickly learn the network topography or it is close to the destination. In [10], the authors combined these two factors and used the following formula to calculate the heuristic value for node j with respect to the sender node i:

$$\left(\frac{1}{h^k}\right)\frac{D\,(i\,,j)}{R}+\left(1-\frac{1}{h^k}\right)\left(1-\frac{D\,(j\,,Finish)}{D\,(i\,,Finish)^k}\right) \qquad (4)$$

where:

$D(i, j)$ - distance between the sender i and its neighbor j,
R - maximum communication radius,
h - number of hops that the message has currently been transmitted (assume h starts with 1)
k - positive constant

To balance the above two unrelated values, both are normalized, where the first term rewards nodes that are far away from the sender and the second term penalizes neighbor j if it is further to the destination than the sender node i, (the case in which the second term is negative). The constant k reflects how rapidly the weight is shifted from picking a neighbor remote from a sensor to picking a neighbor close to the destination. The method tends to pick a sensor closer to the destination as h, the number of hops, increases to prevent the message from being circulated endlessly throughout the sensor network.

The algorithm for localized approximation of minimum exposure path consists of 4 steps:

- the sensor that is closest to the starting coordinate sends a Search message to the node that is determined on the basis of the above heuristic value;
- when this Search message reaches its destination sensor (the sensor closest to the ending coordinate), the sensor calculates the minimum exposure path using a Voronoi-based approximation algorithm and the network's topological information it receives. (The Voronoi-based approximation algorithm gives the near-optimum exposure path within a Voronoi cell without using the grid-based method requiring extensive computational resources and hence reduces the computation requirements);
- next, the algorithm selects the sensor in the location that most probably contains the minimum exposure path and sends a Forward message to this sensor. When the appropriate sensor receives the Forward message, it sends a Search message back to the destination sensor to acquire more information on the sensor network's topography that is needed by the Voronoi-based approximation algorithm;
- this process is repeated until no sensor node requires any further topological information or no locations look promising in comparison to the current minimum exposure path calculated.

The minimum exposure path approach is very useful in the network's evaluation. Once the minimum exposure path is known, the user can manipulate sensors in the network or add sensors to the network to increase coverage.

6. Algorithms for navigation in mobile sensor network

The problem arising after the calculation of the network's coverage is how to navigate nodes effectively in order to move some of them and improve this coverage

[11]. Czapski [12] suggested a fully adaptive routing protocol for the wireless sensor network taking advantage of the nature of sensed events to localization of individual nodes. In [13], the authors described techniques enabling the incorporation of GPS measurements with an IMU sensor. A complementary filter known as the Kalman Filter (KF) provides the possibility to integrate values from the two sources whilst minimizing errors to provide an accurate trajectory of the vehicle. The following GPS and INU data is post-processed by an Extended KF (EKF). In [14], the authors described a multiple sensor fusion-based navigation approach using an interval analysis (IA)-based adaptive mechanism for an Unscented Kalman filter (UKF). The robot is equipped with inertial sensors (INS), encoders and ultrasonic sensors. An UKF is used to estimate the robot's position using the inertial sensors and encoders. Since the UKF estimates may be affected by bias, drift etc., an adaptive mechanism using IA to correct these defects in estimates is suggested. In the presence of landmarks, the complementary robot position information from the IA algorithm using ultrasonic sensors is used to estimate and bound the errors in the UKF robot position estimate.

Using GPS system is costly and power consuming and known collaborative methods of localization based on positions of neighboring nodes also consume plenty of energy and are not precise. In our paper, we consider a network with a dynamically changing number of nodes. Each node can move according to its own kinematics and there is no correlation between them, but their initial positions are known. The task of a navigation algorithm is to estimate the position of each node at all instances in a globally fixed coordinate system. There should be two kinds of measurements: the displacement of each node between two time instances (from inertial unit) and the distance between any two nodes within a certain range at each time instance (from RF measurements). The multi-modal fusion problem can be presented as a graphical model, where nodes represent variables and links represent constraints. The problem is to estimate the values of the variables - representing nodes, given the constraints - representing the links. For estimation of a single value for each variable as the best solution, this can be formed as a maximum a posteriori (MAP) estimation problem.

7. Iterative distribution algorithm

The standard Kalman Filter approach with a distributed iterative EKF formulation provides excellent accuracy and convergence. In the distributed approach, the location of each node estimates an independent computational unit requiring very limited communications overhead to exchange intermediate location estimates with neighbors. This formulation enables practical implementations with minimum location accuracy reduction. Using a standard EKF algorithm, the state vector of each node can be estimated in parallel. However, since the estimation results of one node are strongly dependent on the estimated locations of the other nodes, one pass through the algorithm is not sufficient to accurately estimate the locations of entire network. To solve this problem, Wu and others [15] proposed an iterative distribution algorithm, in which:

- each node estimates its state by using its inertial navigation unit (INU) observation;
- each node obtains RF distance measurements from all the remaining nodes;
- each node exchanges its state estimate with all the remaining nodes;
- the RF distance measurements are used to re-estimate each node's state by EKF.

After multiple iterations of the last two steps, the state of each node will converge to its optimization point. In this manner, the locations of the entire sensor network can be accurately estimated in parallel with virtually no redundant computation and with minimal inter-node information exchange.

The algorithm estimates limit errors in position estimations by continuous fusion of new INU measurements and previously fused location estimations. Position displacements can be determined with MEMS-based INUs and the distance between two nodes can be measured by time-of-arrival TOA-based radio frequency distance measuring sensors. The main underlying assumption of the EKF approach is that the node state can be modeled as a multidimensional Gaussian random variable. This assumption is justified by the fact that an INU measurement gives highly peaked unimodal distribution. The final distribution of the state, after considering the ranging constraints, exhibits a dominant mode (the correct solution) close to the INU peak. Since the distance measurement is not a linear function of the locations, the standard Kalman Filter approach with a distributed iterative EKF formulation that provides excellent accuracy and convergence was used. Since the INU measures the location offset, which is directly proportional to velocity, the filter will have nearly no lag. Moreover, the authors made a few assumptions regarding the node motion and use a simple constant velocity model for prediction, enabling flexible implementation that accepts asynchronous sensor inputs. They postulated the integration of two sensors: INU and distance sensor to estimate absolute and relative positions of sensor nodes. INU sensors prevent geometric ambiguities and distance sensors reduce the drift rate of the individual INUs by a factor of $\sqrt{n}$ by providing mutual constraints on possible position estimates of n collaborating nodes. Collaborative navigation gives improvements of performance in drift-rate reduction and resetting errors of location estimates even after a dynamic change of system conditions.

8. Calculating errors

Considerations of error reduction effects expected when multiple nodes collaborate to determine their locations.

If r_A and r_B are vectors representing the INU-derived estimates of the locations of nodes A and B respectively and r_{AB} is the estimate of the distance from B to A (TOA measurement), then the location of node A can be estimated by the average of INU in node $A - r_A$ or by: $r_B - r_{AB}$. If r_B and r_A have independent errors of size σ_{INU} and the error of r_{AB} is negligible as compared to it, then this average is statistically optimum and has the reduced error of $\sigma_{INU}/\sqrt{2}$. The error can be further reduced when additional nodes collaborate in RF distance measurements. The error of an average of n independent and identically distributed measurements with common error σ! is: $\sqrt{n}$;

$$\text{If } y=\frac{(x_1+\ldots+x_n)}{n} \quad \text{and} \quad x_i(i=1,\ldots,n) \tag{5}$$

are identically distributed measurements with common standard deviation σ_x then:

$$\sigma_y=\frac{\sigma_x}{\sqrt{n}} \tag{6}$$

For a n-sized network with direct communication, a given node has n independent INU location estimates. One estimate is from its own INU; the remaining $n-1$ are based on the INU location estimates of the remaining $n-1$ nodes, the inter-node distance measurements and the previously fused location estimates. A combination of n independent INU estimates provides a $1!/\sqrt{n}$ error improvement. This improvement is independent of the specific multi-sensor data fusion algorithm employed, provided the fusion algorithm is formulated in a way that leverages the principles of averaging independent sensor estimates. It is also independent of specific noise model of the underlying sensor (INU or otherwise) that is used to obtain the base position estimate. In practice, instead of requiring the relative location of B from A, only the distance between them is needed for the scaling result to hold. The use of continuous INU measurements and previously fused location estimates virtually eliminates geometric ambiguities like flips, translations, and rotations.

8.1. Sensitivity to Distance Constraint Error

The derivation of the error-scaling law assumes that the ranging measurement error is negligible compared to that of the inertial measurement to achieve the $1!/\sqrt{n}$ improvement.

The analysis presented in [16] shows that the scaling law improvement is quite insensitive to distance measurement errors and that its effect should hold quite well even as the distance measurement error approaches that of the inertial sensors. Reasonable values of INU and ranging error result in a deviation from the ideal scaling behavior by only a few percent, while a typical worst-case combination yields at most an 11 percent deviation.

8.2. Resetting errors of all location estimates

When nodes with independent self-location estimates come within range of one another for distance measurement, the errors of all their location estimates are immediately reset to lower values. Reset error levels are independent of the history of ranging activities among the nodes and long-term error growth is insensitive to splitting or joining of the group. The errors in incremental node displacement estimates contribute to the errors in the location estimates in an additive fashion. Let Δx_k^i and dx_k^i be real displacement and estimated by INU displacement of node i made between t_k and t_{k+1} respectively. The additive uncertainty associated with this estimate is denoted N_k^i with a common variance σ_{INI}^2 . The location estimates of node i at time t_k are given in [17]

$$x_K^i(1)\int\sum_{k=1}^{K} dx_k^i=\sum_{k=1}^{K}\Delta x_k^i+\sum_{k=1}^{K}N_k^i \tag{7}$$

If at time t_k node i joins a group of $n-1$ other nodes, then, using the independent averaging assumption, the location estimate of node i becomes

$$x_K^i(n)=\frac{1}{n}\sum_{j=1}^{n}[x_K^i(1)+x_{ij}] \tag{8}$$

where x_{ij} is the highly accurate location of node i relative to node j enabled by distance measurement.

Although the position uncertainty of a node in a small group may grow while the groups are separated, it is immediately reset to the appropriate lower value when the groups merge to form a larger group.

8.3. Evaluation of performance

Analytical prediction of these multi-sensor fusion algorithms should be checked using some simulations. In [17], the authors gave a few formulas for the evaluation of the algorithms' performance. Absolute and relative RMS errors can be calculated using the results of Monte Carlo simulations. The absolute RMS error vector of the entire network at t_k will be

$$\varepsilon(k)=\sqrt{\frac{1}{mn}\sum_{l=1}^{m}\sum_{i=1}^{n}\hat{x}_i^l(k)-\bar{x}_i^l(k))^2} \tag{9}$$

$$\text{where } \varepsilon(k)=[\varepsilon_x(k),\ \varepsilon_y(k),\varepsilon_z(k)],\hat{x}_i^l(k),\bar{x}_i^l(k) \tag{10}$$

are the estimated locations and real locations, respectively, of the i^{th} node in the l^{th} Monte Carlo run; and m is the total number of the runs.

The relative averaged RMS error can be defined as

$$\bar{\delta}(k)=\frac{1}{m}\sum_{l=1}^{m}\sqrt{\frac{1}{n(n-1)}\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}(\hat{d}_{ij}^l(k)-\bar{d}_{ij}^l(k))^2} \tag{11}$$

where $\hat{d}_{ij}^l$ and $\bar{d}_{ij}^l$ are the estimated distance and real distance, respectively, between nodes i and j at time t_k from the l^{th} run.

9. Conclusions

Calculation of exposure is one of fundamental problems in wireless ad-hoc sensor networks. This paper introduced the exposure-based coverage model, formally defined the exposure and analyzed several of its properties. An efficient and effective algorithm for minimum exposure paths for any given distribution and characteristic of sensor networks was presented. The minimum exposure path algorithm developed as a localized approximation algorithm was chosen for planned network of numerous small mobile sensor nodes used for monitoring of large terrains. The algorithm works for arbitrary sensing and intensity models and provides an unbounded level of accuracy as a function of run time. It works even after a few nodes of network are damaged and requires minimum consumption of energy. The second problem arising after the calculation of the network's coverage is to move some of the nodes in order to improve this coverage and to navigate nodes effectively (also in GPS-denied areas). Position displacement can be determined with micro-electromechanical system-based INUs. As the author of [18] convinces us, for many navigation applications, improved accuracy/performance is not necessarily the most important issue, but meeting performance at reduced cost and size is definitely vital. In particular, small navigation sensor size enables the introduction of guidance, navigation, and control into applications previously considered out of reach. In recent years, three major technologies have enabled advancements in military and commercial capabilities. These are Ring Laser Gyros, Fiber Optic Gyros, and Micro-Electro-Mechanical Systems (MEMS). The smallest INUs presented have the size of 3.3 cc. Distributed fusion of multiple independent sensors using the suggested navigation algorithms can exploit the complementary nature of each sensor-nodes characteristics for overall improvements in system accuracy and operational performance without sacrificing operational flexibility, estimating both absolute and relative positions for the members of a mobile sensor network by continuously fusing pair-wise inter-node distance measurements and the position displacement measurements of individual nodes. The benefits of the collaborative error reduction can be realized without use of anchor reference nodes and also with as few as two sensor nodes.

It is likely that progress in computing and sensing technologies will soon determine new criteria for algorithms of mobile sensor-nodes and, therefore, in our future works, we plan to make adequate simulations with both algorithms working simultaneously on sensor nodes with different environment parameters.

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