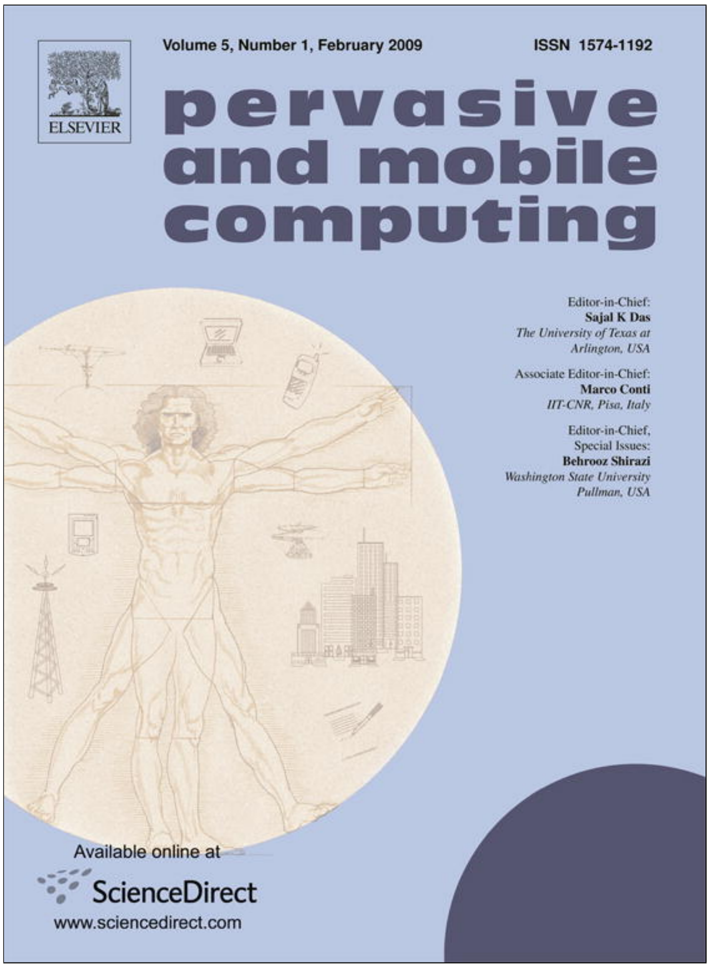
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Fast track article

Gradient-based target localization in robotic sensor networks

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ABSTRACT

Fast target localization without a map is a challenging problem in search and rescue applications. We propose and evaluate a novel gradient-based method which uses statistical techniques to estimate the position of a stationary target. Mobile nodes can then be directed toward the target using the shortest path. Moreover, localization can be achieved without any assistance from stationary sensor networks. Simulation results demonstrate nearly a 40% reduction in target acquisition time compared to a random walk model. In addition, our method can generate a position prediction map which closely matches the actual distribution in the field. Finally, experiments have been performed using MicaZ motes which further validate our techniques.

1. Introduction

Recently, applications of wireless sensor networks have gained extensive attention in many areas such as tracking, surveillance and environmental monitoring [1–3]. Moreover, hybrid systems of mobile objects (i.e., robots) and sensor networks create new frontiers for civilian and military applications, such as search and rescue missions in which the background environment is inaccessible to humans. Systems combining distributed computation and communication together with navigational capabilities are likely to be widely deployed in the future.

The challenging problem we address in this work is *to rapidly and accurately navigate a team of mobile sensor nodes toward a stationary target while consuming the least amount of energy*. Previously, most research groups have employed static wireless sensor networks to navigate the mobile sensor nodes. For example, Tan in [4] used a distributed static sensor network to collect data and to execute local calculations. Based on this information, a path could be generated for a set of mobile nodes to move toward a specific goal. Although the in-network calculation implemented in that project was quite efficient in creating the shortest routing path, the requirement of an additional stationary distributed sensor network sets a barrier for rescue applications because of the high cost to cover a large geographic area with a number of sensors. Another group [5] has proposed gradient methods in which the mobile wireless sensor nodes move along the gradient direction toward a target. However, in all of these implementations, the assistance of a stationary wireless sensor network was assumed to be available in generating a local signal distribution map. A probabilistic navigation algorithm is presented in [6], where a discrete distribution of vertices is introduced to point in the direction of movement. Their model is Markovian, in that the next state of a robot depends only on the current state and current action. The navigation problem is modeled as a Markov Decision Process in which the vertex is calculated by a value iteration algorithm. This algorithm computes the utility for each state and then selects the action which yields a path toward the goal having the maximum expected utility. The shortcomings

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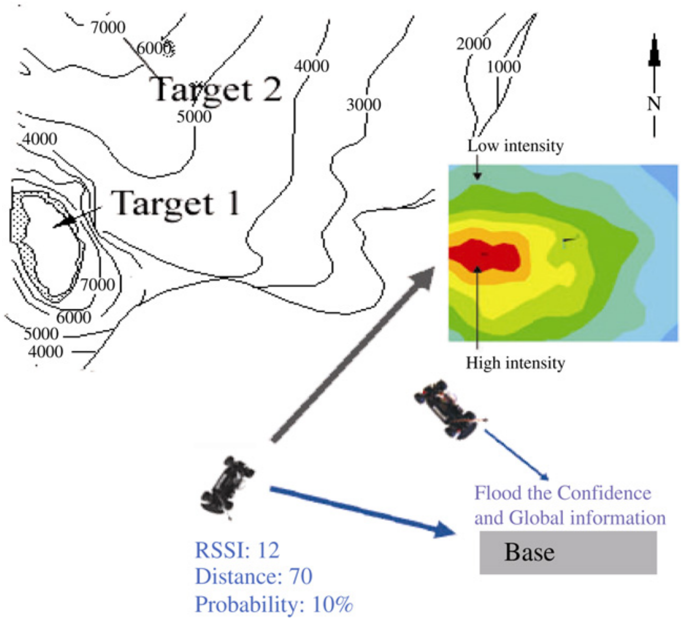

Fig. 1. Mobile sensor nodes enter a target area, maintaining communication with a base station.

of this method are that it requires the arrival of a mobile sensor node to localize the target position and it will introduce significant communication overhead during the iterative process.

In this paper, we overcome these limitations by incorporating a prediction model of real-time processes into a mobile sensor network architecture. We are interested in the mutually beneficial collaboration of the algorithms described above but seek to reduce their costs and provide faster target localization. *The novelty of our approach is the integration of a per-node prediction model with a global prediction model.* The per-node prediction model guarantees that a mobile node can acquire the position of a target alone, while the global prediction significantly reduces the navigation overhead and time through collaboration with other nodes.

Our model provides a more meaningful description and utilization of individual sensor information by taking into account their accuracy and confidence level. Furthermore, our model works with a single mobile sensor node as well as a swarm of mobile sensor nodes. In the latter case, the sensor nodes have the ability to share local information in order to draw a global picture, which helps each sensor node to acquire the target along a significantly shorter path. Finally, the in-network prediction algorithm enables faster yet accurate target position acquisition: sensor nodes would be required to reach the target only when the model prediction is not accurate enough to satisfy the requirement with an acceptable confidence. This allows a significant reduction in navigation energy. A preliminary description of some of this work was presented in [16].

The remainder of the paper is organized as follows. In Section 2, we describe the basic structure of our prediction model. Section 3 continues this discussion by providing the mathematical details used in the design of the system. The collaborative prediction algorithm is described in Section 4. Section 5 presents the experimental procedure that has been used to calibrate the model as well as simulation results for the performance of our system. This is followed by a discussion of the optimization issues involved and the lessons which have been learned in this study, as well as a discussion of related work. Finally, our conclusions and future research objectives are given.

2. Prediction model structure

We assume that every sensor node can act as both a remote sensor and as a network relay. Several methods have been proposed to accomplish this. For example, IGF [9] provides a routing scheme to maintain connectivity among mobile sensor nodes. In [10], back-up sensor nodes have been shown to provide extra energy-saving benefits aside from maintaining the global network framework.

Furthermore, if a mobile sensor node enters an unknown area, it must be able to determine its own location, such as through GPS, as in ZebraNet [7] and VigilNet [2]. Alternatively, a dynamic localization scheme [8] may also be used which adjusts the estimated location of a node periodically based on its recent motion.

The main goal of our gradient-based target acquisition scheme (which we call GraDrive) is to predict the location of stationary targets within an allowable uncertainty or confidence level. A typical scenario is depicted in Fig. 1. Our method can be briefly described as follows: The control center (i.e, base station) disseminates a search objective to a mobile sensor network with two parameters, the *error tolerance* and the *confidence level* of the target. These factors specify the desired quality of the target acquisition process. For example, an objective could be to locate a target within 2 m with at least 95% confidence. The tolerance levels for each mobile sensor node may be assigned on a per-node basis if different nodes have been designed for different purposes. Once the individual nodes have received a request for target acquisition, each one

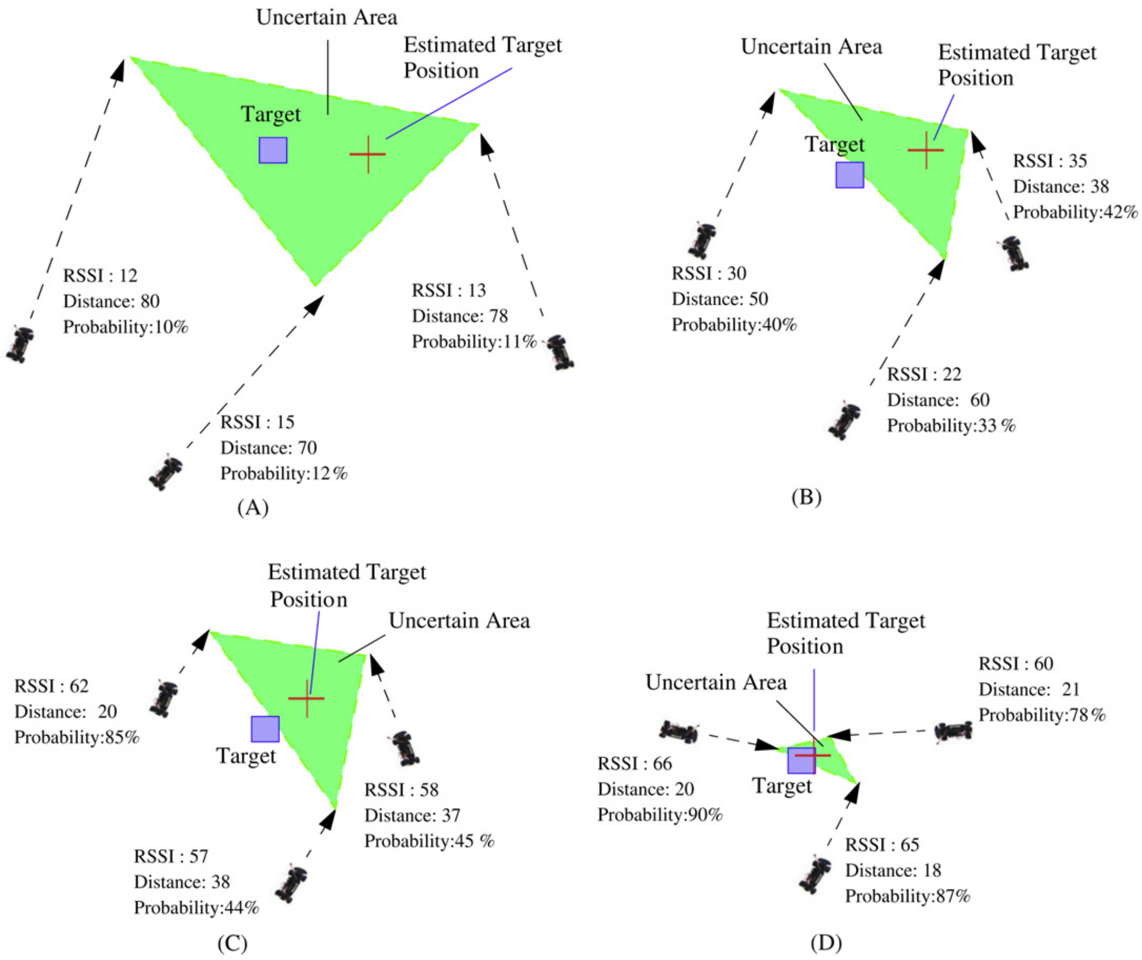

Fig. 2. Collaborative prediction scheme of GraDrive.

determines the most efficient way to locate the potential target with the requested tolerance levels. This process occurs *individually* at each mobile sensor node using a per-node prediction model. In particular, a node starts to move in the direction which it anticipates is the shortest path to reach the target.

In addition to its own plan and navigation, sensor nodes also report back to the base station, where all the individual nodes' readings and plans are collected in order to create a global map and an uncertainty area. Then, the base station can disseminate global prediction data over the network so that each sensor node can update its own model accordingly. Each individual sensor node continuously predicts the target position with increasing accuracy as it moves toward the target. This process is illustrated in Fig. 2, where the progression from scene (A) to scene (D) shows how the area of uncertainty shrinks as the mobile node approaches the target. Thus, our system uses dynamic, cooperative processes to direct its operation as opposed to using a static navigation plan [6,11].

3. GraDrive model details

In this section, we formally describe our per-node prediction model to estimate the position of a stationary target with a given confidence. This per-node prediction model forms the basis for global collaborative prediction described in Section 4. In general, we allow an unknown area having multiple targets. However, the search for each separate target is independent as long as the field generated by one target doesn't overwhelm that generated by others. Therefore in the remainder of this paper, we focus on only the single target acquisition problem.

3.1. Formulation

We begin with a value-prediction problem, which creates a Received Signal Strength Indicator (RSSI), $F(\theta)$, over a parameter set θ. For example, if $\theta = (d, t, v)$, RSSI is related to d, the distance between a mobile sensor node and the target, t, the time of sampling, and v, the speed of the mobile sensor nodes. This model can be established by obtaining consecutive sensing readings (system states) as a mobile sensor node moves. Typically, the number of parameters in θ is much less than the number of states collected and changing one parameter changes the estimated value of many states. To approximate our model appropriately, we seek to minimize the mean squared error over some distribution, P, of the inputs. In our value-prediction problem, the inputs are states which include sensor node position and predicted target position information. The target function is the true RSSI F^{π}, so the mean squared error (MSE) for an approximation F^{T}, using parameter θ, is

$$MSE(\theta) = \sum p_i (F_i^{\pi} - F_i^{T})^2 \tag{1}$$

where p_i is a distribution weighting the errors of different states. We need the distribution function because it is usually not possible to reduce the error to zero for all inputs, as there are generally far more states than components in θ. Better approximation at some states can be gained generally only at the expense of less accuracy for other states.

3.2. Remoteness prediction model

In GraDrive, we use a Gaussian distribution of two variables. The predicted distance from the sensor nodes' current position to the predicted target position can be queried or estimated from the model. The multidimensional Gaussian distribution function over two attributes, trust interval and RSSI, can be expressed as a function of two parameters: a 2-tuple vector of means, μ, and a 2×2 matrix of covariances, Σ. Further, we assume the trust interval set by a rescue team is independent of the RSSI received, which means the trust interval of the predicted distance estimation T_i to the mean of historic results μ doesn't change dynamically during the search process. Without loss of generality, it is assumed that the predicted distance d is inversely proportional to RSSI: $d = r_1/RSSI + r_2$, where r_1 and r_2 are two adjustable parameters that can be determined prior to the searching process. We note that other RSSI attenuation models can be used here as well without invaliding our approach. We then use historical or experimental data to construct the models, providing appropriate values of r_1 and r_2 at each RSSI value.

In addition to determining the predicted distance, a probability model is also constructed in order to provide the confidence level of the prediction. For example, given a predicted distance of 2 feet, the confidence level for this prediction may be 95%. The model must be trained before it can be used, which is a limitation of any probabilistic model. The accuracy of the model, therefore, depends on the accuracy of data used to train it. Once the initial model is constructed, each sensor node can query the predicted distance map and come up with a confidence value. One distribution of the distance d against the confidence p over one RSSI is a Gaussian distribution. Suppose that a rescue team has set a trust interval of T_i. Given the distribution of distance over one RSSI, we can find the points d_i which satisfy $P(d_i) - P(u) \leq T_i$. Here we emphasize that if the trust interval is too small, the amount of data needed to train the model will increase significantly.

3.3. Prediction model of signal strength distribution

Aside from obtaining the distance d information based on measured *RSSI*, we can further refine the RSSI distribution model. This model can then be used to navigate the mobile sensor network toward the target on a shortest path. The central element in our approach is to construct a prediction model that represents attributes as accurately as possible in a mobile sensor network. As discussed above, if the predicted RSSI distribution function depends on parameters including distance d and confidence or probability p, the function can be expressed as $F(d, p)$. Assuming that the distributions for d and p are independent, we then have:

$$F(d, p) = f(d_0, d_1, d_2, \ldots)f(p) \tag{2}$$

where the d_i are related to the distance variable d. To reduce the energy needed to perform the computations, only a second-order expansion is considered here, which leads to the 3-component vector $D = [d_0, d_1, d_2]$:

$$\begin{aligned} d_0 &= c_0 \\ d_1 &= 1/(d + c_1) \\ d_2 &= 1/(d^2 + c_2) \end{aligned} \tag{3}$$

where c_1, c_2, c_3 are constants included to avoid having a singularity at $d = 0$. Now we can define our gradient distribution function in the following compact format:

$$F = DAp \quad \text{where } A = [a_0, a_1, a_2]. \tag{4}$$

Eq. (4) is our probabilistic gradient distribution prediction function given the attributes d and p. Suppose that each sensor node observes the value of attribute D_j to be d_j. We combine the input sensor values into a vector D_j. Then, a set of these vectors is assembled into the matrix shown below:

$$D = \begin{vmatrix} d_{00} & d_{10} & d_{20} \\ d_{01} & d_{11} & d_{21} \\ \cdots & \cdots & \cdots \\ d_{0n} & d_{1n} & d_{2n} \end{vmatrix}. \tag{5}$$

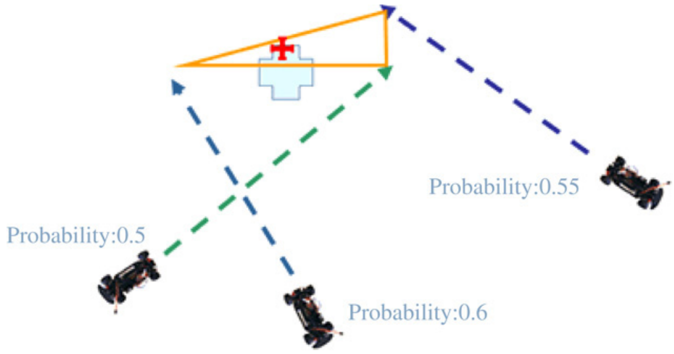

Fig. 3. Example of the probability weight average localization algorithm.

If enough sensor readings are provided, we can apply nonlinear least squares fitting to estimate the parameters A. To accomplish this, linear least squares fitting may be applied iteratively to a linearized form of the function until convergence is achieved. Since we can anticipate a power-law type of fit and already have selected initial parameters values for our models, the nonlinear fitting process has good convergence properties.

Perpendicular least squares fitting proceeds by finding the sum of the squares of the actual deviations of a set of data points to achieve the following minimum:

$$\min\left(\sum\left(F_i^{\pi}-(a_0d_{0i}+a_1d_{1i}+a_2d_{2i})\right)^2\right). \tag{6}$$

The square deviations from each sensing sampling point are therefore summed, and the resulting residual is then minimized to find the best fit for the sensing reading. This procedure results in the outlying points being given disproportionately large weight.

In general, the computation of such a matrix may consume a large amount of a wireless nodes' energy. The solution in GraDrive is to simplify the prediction distribution function as above, given that the prediction function computation can be distributed over the network with collaboration of its neighbors or the data to be delivered back to a base station where the computational ability and energy are normally not limitations. If this is the case, the base station creates a gradient distribution map globally using a weighted average method as a function of probability and predicted distribution. This kind of global information is then sent back to each individual node in the system.

4. Collaborative prediction in target localization

Based on the per-node prediction model, the mobile sensor nodes can infer the target position (x, y) and the associated confidence value p. This information is then used to perform global predictions. Specifically, we propose to use a probability-weighted average model for global collaborative prediction, due to its high efficiency and low cost. The rationale behind our method is that the sensor nodes having a higher probability are much closer to the intended target. An example of this model is illustrated in Fig. 3, where the position of the target is estimated within the triangle formed by the three per-node prediction results.

Let the predicted target locations provided by sensor nodes $n_1, n_2, \ldots, n_k$ be $(x_1, y_1), (x_2, y_2), \ldots, (x_k, y_k)$, with probability values $p_1, p_2, \ldots, p_k$, respectively. The estimated position of the target is then given as:

$$X=\frac{\sum_{i=1}^{k}p_kx_k}{\sum_{i=1}^{k}p_k}Y=\frac{\sum_{i=1}^{k}p_ky_k}{\sum_{i=1}^{k}p_k}. \tag{7}$$

4.1. Collaborative navigation for mobile sensor nodes

With per-node and global prediction models established, we are now ready to describe how the sensor nodes navigate using these two models. There is no assumption that the sensor nodes know the map before entering. The flexibility provided to the mobile sensor nodes should not be an issue when considering our navigation protocol, because it is in general designed for an active navigation application. We simply assume that the mobile sensor nodes can rotate at any angle at any position. Algorithm 1 illustrates the proposed navigation plan for the mobile sensor nodes. This algorithm requires inputs from both local sensor nodes and the base station. Local sensor nodes calculate their direction of movement by using local information sensed by itself or global information broadcast by the base station.

Initially, sensor nodes enter a region of interest with certain speeds, directions and confidence intervals. It should be noted that different mobile sensor nodes may have different speeds or initial directions. A default navigation plan is used, which is to keep moving forward unless a node detects a smaller RSSI reading. During the motion, nodes themselves perform

Algorithm 1 Navigation of mobile sensor nodes and prediction

```
Suppose mobile sensor node A enters the unknown area with a random direction
Global prediction = N/A
repeat
  Node A checks the sensed RSSI, stores the value and reports it to the base
  if the confidence of global prediction > a certain threshold then
    next navigation direction = the direction of global prediction;
  else if Current Sensed RSSI > Last Sensed RSSI then
    Keep moving;
  else
    Rotate counterclockwise 90° and keep moving;
  end if
  Predict the target location and associated confidence using RSSI
  A base station collects all the predictions generated by individual nodes and merges them into a global prediction.
  if The changes in global prediction > a certain threshold then
    Disseminate the global prediction to all nodes.
  end if
until Target Acquisition Confidence reaches the dictated objective
Report the target position;
```

per-node prediction calculations to construct the local RSSI map as described in Section 3.3. Meanwhile, the sensor nodes estimate their distance to the target position according to the sensed RSSI, randomly selecting one prediction within its confidence interval. The predicted target location information is forwarded back to a base station. To prevent excessive energy consumption in communication, the frequency of updates can be specified in advance. As long as the global picture is not available, individual sensor nodes navigate according to the per-node prediction model. However, if the base station notifies the sensor nodes that it has constructed a global RSSI distribution with certain confidence, each sensor node will combine the information with its current model and change its direction toward the gradient direction. This process will be repeated until the target position has been discovered locally or at the base station within acceptable confidence.

4.2. Default navigation plan

If initially there is no global picture constructed by the base station with acceptable confidence, or if the network is partitioned or unable to deliver the data, the mobile sensor nodes fall back to the per-node prediction model. Its current sensor reading is compared with previous readings stored in memory at each motion step. If it detects a smaller RSSI, it rotates 90 degrees clockwise as shown in Fig. 4, since the the target position is most likely located perpendicularly to its previous direction of movement.

5. Experimental setup and simulation

5.1. Model fitting experiment

In order to verify the feasibility of the proposed prediction model and parameter-fitting algorithms, we have prototyped a light sensing system based on Berkeley MicaZ motes, as shown in Fig. 5. Even though it is stationary, the prediction model and parameter-fitting algorithms can still be verified at the base station site which can be transferred to individual sensor nodes and implemented. Light signal strength is used as an example of RSSI to feed the model. One laptop equipped with motherboard acts as the base station. A lamp is used as a target and a series of sensor nodes are deployed. The sensor nodes detect the sensing reading and exchange the readings to their neighbors. The base station calculates the parameters for the sensor nodes by using the least square fitting method. Fig. 6 shows one set of data fitted by the prediction model. The distance between two adjacent sensor nodes is equal and unified for matching purposes. Since the received signal strength is not an accurate measurement, the probability approximation model comes into play. From the matching results, it is shown that the least squares method tries to reduce the deviation among the sensing data collected. Other sets of data can also be collected and used to train the model before it can be applied to the mobile sensor scenario.

5.2. Simulation setup

We have developed a program to verify the advantage of using our prediction model to locate the target. In our simulation, a 200×200 m^2 area is regarded as an unknown space with a target located at the center and an initial distribution is specified. Essentially, it could be any random distribution that having a gradient toward the center. Each distance unit is represented as the smallest unit that the mobile sensor nodes can travel in one unit of simulation time. The navigation algorithm is used

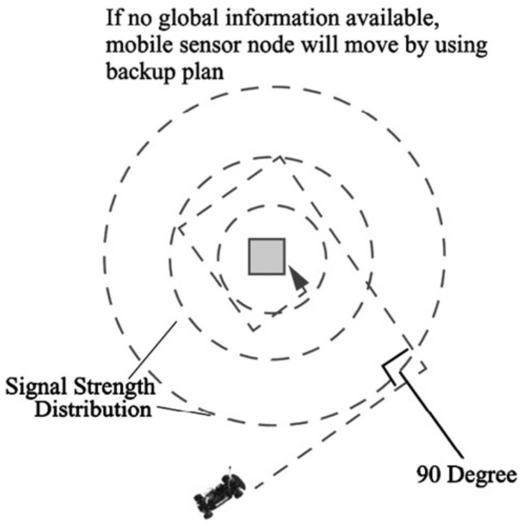

Fig. 4. Default navigation plan for individual sensor node.

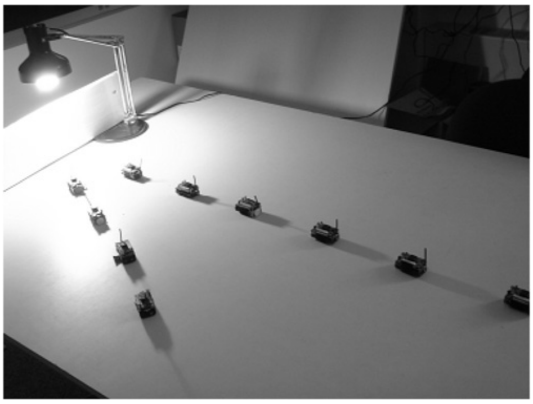

Fig. 5. Model fitting experiment with light as a signal source and using MicaZ motes in array to sense the signal strength.

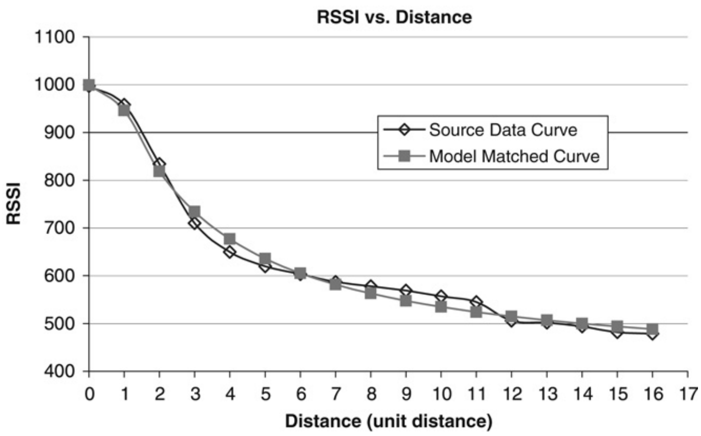

Fig. 6. The predicted model with real sensing data.

to simulate the mobility of objects. Initially, the mobile nodes are located at the edges of the area. The initial direction is randomly picked by each mobile sensor node. If a nodes reaches the boundary of the simulation region, it simply reverses its direction to move back into the allowed area. Under simulation, each mobile sensor node moves at a constant speed in integer multiples of 1 m/s. After a unit of time (1 s in our case) has elapsed, a node recomputes its direction of movement according to the algorithm.

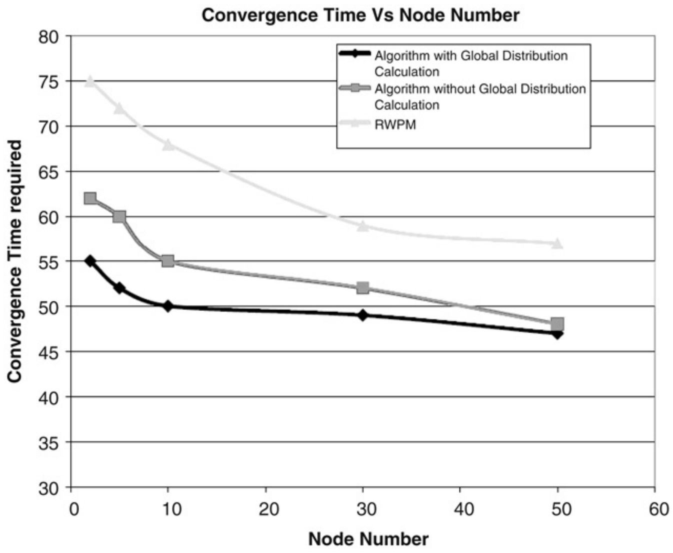

Fig. 7. Convergence time with node number for different models.

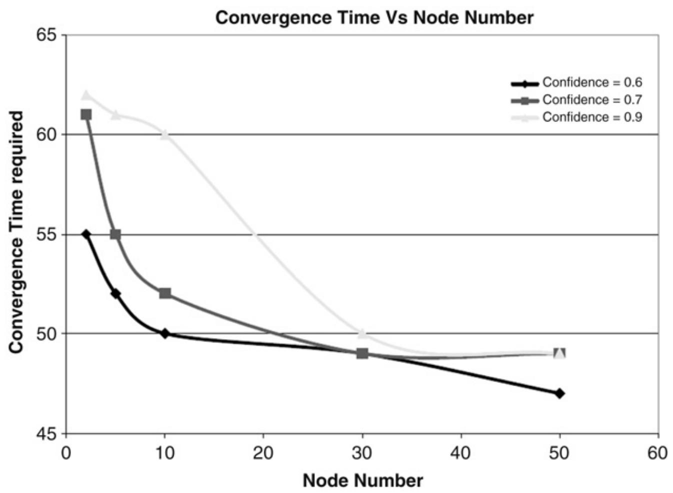

Fig. 8. Convergence time as a function of the number of nodes for different required confidence levels.

5.3. Delay in target acquisition

We first compare our algorithm (without the global distribution calculation option) against a random way point model (RWPM). The simulation results (Fig. 7) suggest that even without using the global distribution calculation, our default procedure (i.e., rotating 90 degrees counterclockwise) provides 30% faster estimation than with the RWPM method. The process operates even faster if the global information is available.

5.4. Impact of the Confidence p

We also compare the impact of different required confidence levels on the convergence time, as shown in Fig. 8. It is clear that if the required confidence level goes beyond 90%, it will take much longer to simulate simply because it requires at least 2 nodes to get very close to the target position. It is reasonable to choose a relatively high confidence level, e.g. 80%, in order to balance accuracy and time cost.

5.5. Impact of the target speed

In Fig. 9, we further investigate the relationship between the speed of the sensor nodes and the prediction accuracy of the target location. The convergence time correlated directly with the speed of each sensor node since the average time for sensor nodes to get closer to the target is reduced. However, the accuracy of the prediction becomes worse if the speed increases because the minimum deviation for the prediction is increased as well. Therefore, the error continues to grow in the prediction as a node moves faster away from its original location. In the situation of high speed, an accuracy error larger

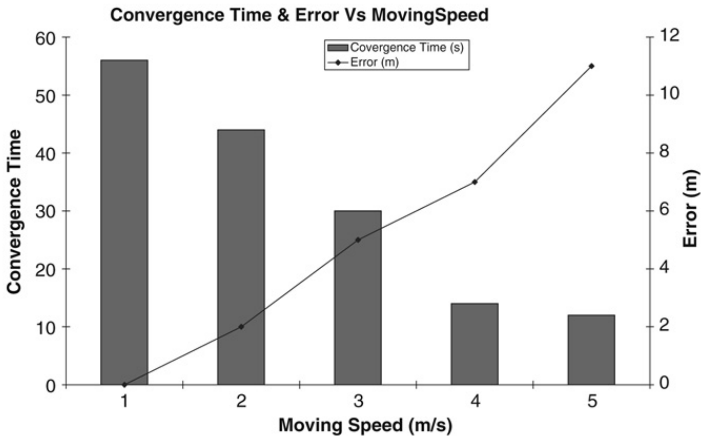

Fig. 9. Convergence time and accuracy with different moving speeds of mobile sensor nodes.

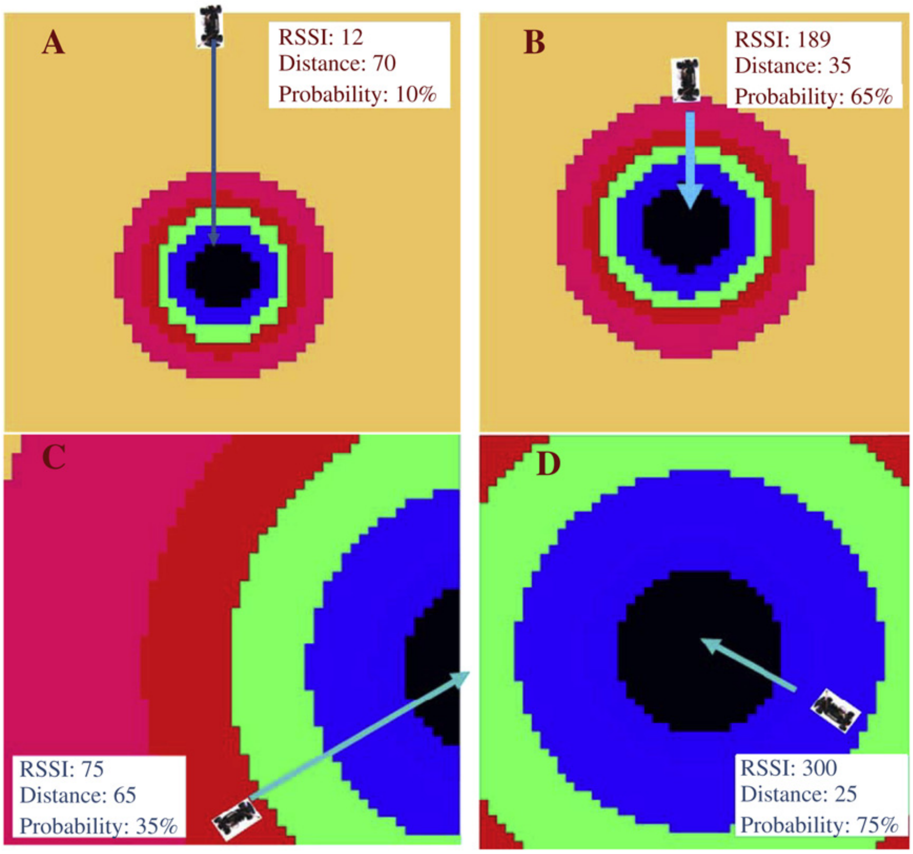

Fig. 10. Examples of sensors prediction by using probabilistic model. (A) and (B) show the same node's prediction at different locations. (C) and (D) show another node's prediction at different locations.

than 10 units is shown. To protect against inaccuracies in the prediction model of mobile sensor nodes, a user must set a limit for the speed of sensor nodes.

5.6. Case study of global information distribution

Fig. 10 illustrates one example of the calculation of our prediction model. A sensor node starting far away from the target location tends to have a conservative prediction and a low probability due to the low signal strength it detects. The predicted probability increases nonlinearly with the sensed signal strength. A similar example is obtained for another sensor node that has a different direction of movement, as shown in Fig. 10(C) and (D). The prediction result for it tends to be more aggressive given its larger sensed signal strength. A rotation event is then triggered when it detects that the RSSI has become reduced. A new prediction process starts immediately when using the default plan. The prediction results at this stage are processed

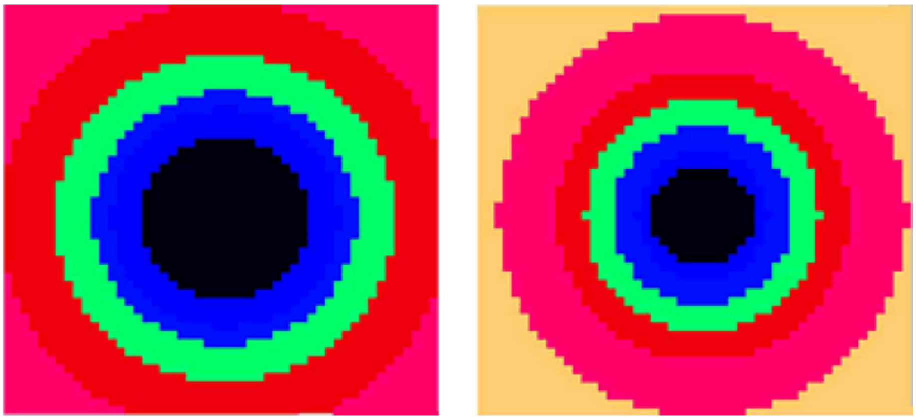

Fig. 11. Example for global signal strength distribution and its prediction results calculated at the base station by combining prediction results from 2 sensor nodes. The plot on the left is the actual distribution while the one on the right is the prediction.

together at the base station, and a global signal strength distribution is generated as shown in Fig. 11. Compared with the real distribution, it is a precise approximation in terms of the gradient direction and the target location prediction.

6. Optimization and lessons learned

This section describes the key optimizations that can be applied to the existing design and some insights obtained in the course of this work.

6.1. Global strength signal distribution calculation

Our global signal strength distribution calculation is done by a central base station due to the required complex matrix calculations. This process transfers most of the calculational burden to a central station where energy usually is not a problem. However, it could potentially induce a significant delay if the search area is large. Thus, use of highly efficient local calculations is an important characteristic of successful implementations of our model.

6.2. Accuracy of target localization

In our model, we assume that mobile sensor nodes can recognize their position through motion estimation. Then, they use their localization information to estimate the target position. One problem is that we haven't been able to reduce the impact of high movement speeds on the accuracy of target estimation. Since we have found that a sensor node at low speed can provide high accuracy of estimation, it is wise to reduce the speed of a sensor node as it gets close to the target position.

6.3. Mobile target acquisition

Although we have described our GraDrive algorithm in the context of a stationary target acquisition, we expect that our design can be extended to a mobile target acquisition scenario as well. In the mobile target case, the global prediction could be invalidated very quickly. Therefore, it is desirable to build a more accurate per-node prediction model to reduce the communication overhead involving global updates. In addition, it is critical to analyze the resource requirements in terms of communication and navigation overhead under different target speeds. More advanced group-based navigation protocols must be developed to precisely identify the target location within a minimal amount of time.

7. Related work

RSSI has previously been used for estimating the distance between a sender and receiver. In the RADAR system [12], RSSI is used to build a centralized repository of signal strengths at various positions and then dynamically determine the location of a mobile unit. In [13], the localization problem is formulated as a real-time estimation in a nonlinear dynamic system and a Robust Extended Kalman Filter is proposed to provide a solution. In [14], the limits of RSSI in terms of localization accuracy and computational requirements are presented.

Several other methods for localization in mobile sensor networks have also been proposed. The use of a mobile beacon with in-ranging is proposed in [17], in which the beacon uses GPS in order to determine localization information. An event-based approach using static sensors and a small number of mobile robots has been described in [18]. Ref. [19] proposes the use of mobile anchor points to implement a range-free system. A potential-based partitioning algorithm for localization in a hybrid network consisting of fixed sensor nodes and mobile robots has been presented in [20,21]. The TARANTULAS system described a system of sensors and actuators in which the static nodes provide landmarks for the mobile nodes [22]. A method using extremely low frequency magnetic fields for localization is presented in [23]. Ref. [24] uses acoustical techniques to locate and track targets.

Navigation is another challenging topic in mobile wireless sensor networks. Most previously developed navigation techniques require stationary sensor nodes that have already been deployed in the field. In the Flashlight System [15], the sensor network models signal strength across an area by introducing an artificial field. The field strength is determined by collecting navigational information from the sensors in the local region. Ref. [25] processes GPS and other information from fixed points using a continuous-discrete extended Kalman filter to assist in robotic navigation. However, in many navigation cases such stationary auxiliary systems are not available. The navigation information gathered from a few local sensor nodes does not fully utilize the computational capability of the entire distributed sensor network. The advantage of our approach is that the combination of per-node and global prediction models can significantly reduce the inaccuracy existing in each individual sensor node.

8. Conclusions and future work

In this paper we have presented a probabilistic prediction model and algorithm for dynamic target localization. Our model does not require any map to determine the positions of the targets. Also, the proposed gradient driven algorithm leads to a 40% reduction in time compared to that of a random path model. The relationship between sensor density and convergence time can be used as a guideline for planning the deployment of a mobile sensor network. While the computational energy requirements may be significant, the error of the predicted target position can be driven to almost zero in a short period of time. For our future work, we would like to design a speed self-adjusting algorithm so that a sensor node has the ability to trade-off performance and cost.

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