Gradient-Driven Target Acquisition in Mobile Wireless Sensor Networks

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Two important conceptions

- Gradient
- Wireless Sensor Network

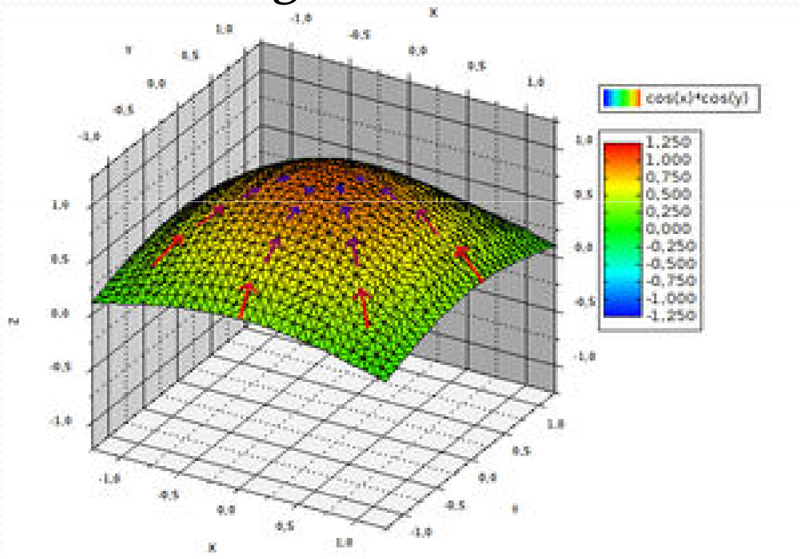
Gradient

- What does it mean?

In vector calculus, the **gradient** of a scalar field is a vector field which points in the direction of the greatest rate of increase of the scalar field, and whose magnitude is the greatest rate of change.

- Example:

A hill, The gradient of *H* at a point is a vector pointing in the direction of the steepest slope or grade at that point.

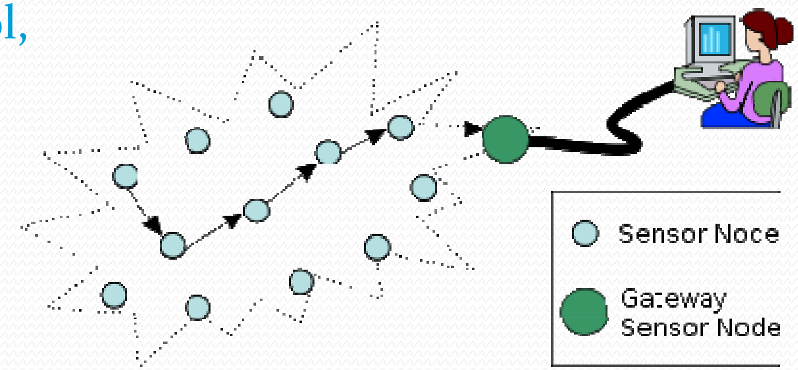


(Source: http://en.wikipedia.org/wiki/Gradient)

Wireless Sensor Network

- A **wireless sensor network** (WSN) is a wireless network consisting of spatially distributed autonomous devices using sensors to cooperatively monitor physical or environmental conditions, such as temperature, sound, vibration, pressure, motion or pollutants, at different locations.

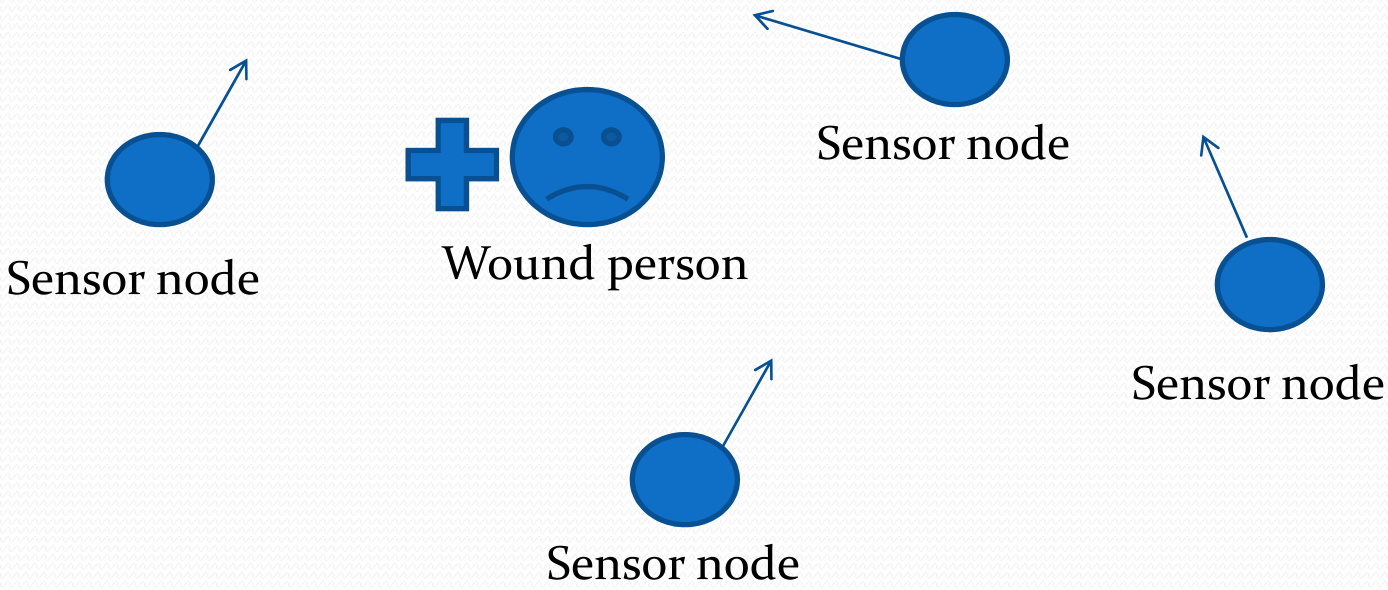
object tracking, nuclear reactor control,
fire detection, and traffic monitoring



Source:
http://en.wikipedia.org/wiki/Wireless_Sensor_Networks

Goal

- Use wireless sensor network to estimate the position of a stationary target and to direct mobile nodes towards the target along the shortest path.



Several Conceivable Methods

1.Distributed static sensor networks:

Execute local calculations to generate a path for a mobile sensor network to move toward the goal.

It's efficient to do the calculation, however, high cost to cover a large geographic area with a large number of sensors.

Several Conceivable Methods

2. Gradient methods in which the mobile wireless sensor nodes move toward the gradient direction assuming that targets carried the most intensive strength of interested signals.

However, in all of their implementations, the assistance of a stationary wireless sensor network was assumed to be available in generating a local signal distribution map.

Several Conceivable Methods

3. Probabilistic navigation algorithm

A discrete probability distribution of vertex is introduced to point to the moving direction. This algorithm computes the utilities for every state and then picks the actions that yield a path toward the goal with maximum expected utility.

It requires the arrival of a mobile sensor node to localize the target position and significant communication overhead is introduced by the iteration process.

Solution to the previous deficiencies

- Incorporating a prediction model of real-time processes into a mobile sensor network sensing and navigation architecture.
- Seamless integration of a per-node prediction model with a global prediction model.

The advantages of our model

- More meaningful description of individual sensor readings in term of accuracy and confidence;
- Works with a single mobile sensor node as well as a swarm of mobile sensor nodes;
- 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.

Two Assumptions:

- **1.Network connectivity**

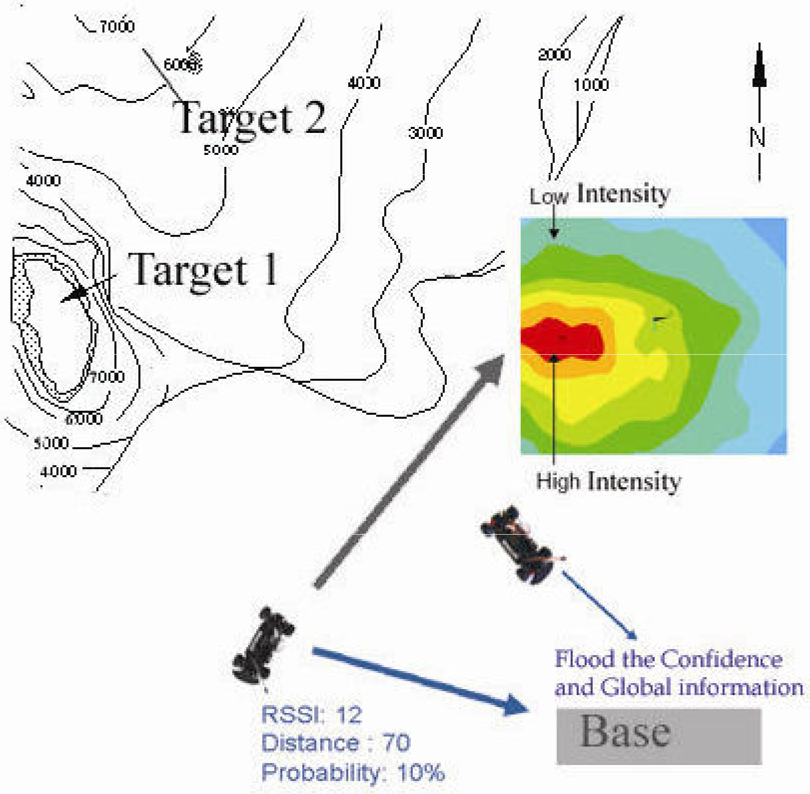
  Wireless sensor nodes in the network are assumed to be able to ensure connectivity.

- **2. Self-localization of mobile wireless sensors**

  If a mobile sensor node enters an unknown area, it must be able to specify its own location dynamically without a map.

Overview

Control center (base) disseminates a search objective to a mobile sensor network with two parameters, **error tolerances** and **confidence level** of the target, specifying the quality of target acquisition.



Overview

- Two prediction models:

1. **Individual Prediction Model:**

   Make own decision

2. **Collaborative Prediction Model:**

   Teamwork

Overview

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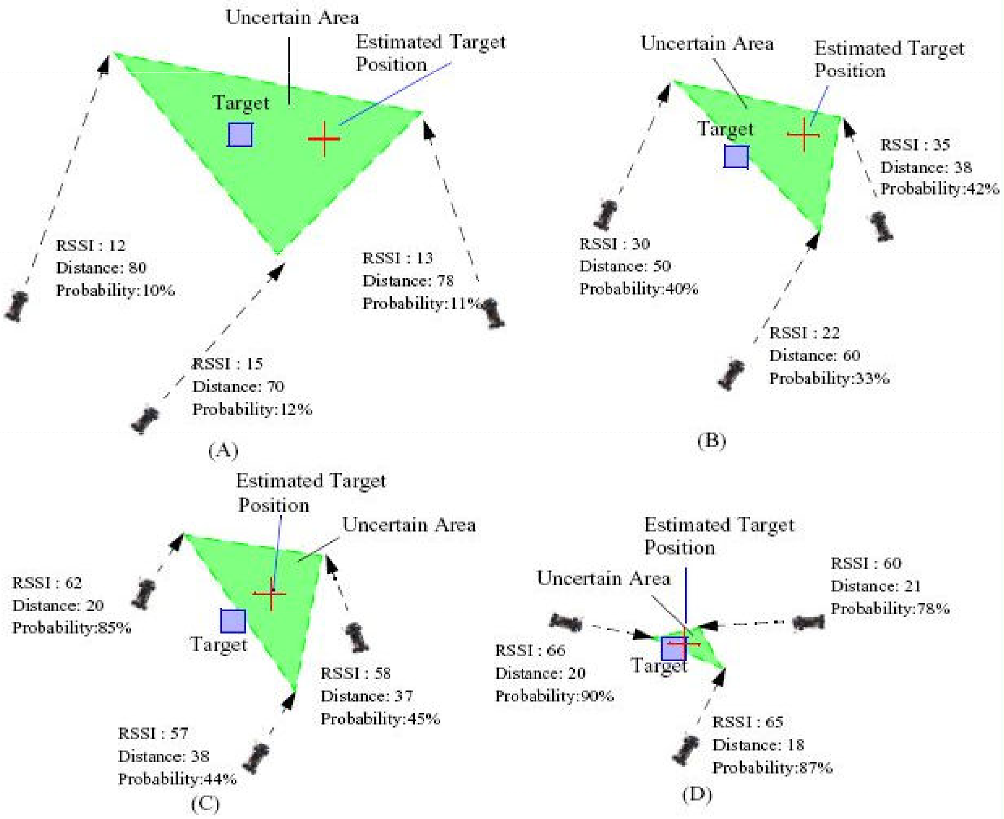


Fig. 2. Collaborative Prediction Scheme of GraDrive

Gradrive Model Details

1. Prediction Problem Formulation

We creates a Received Signal Strength Indicator(RSSI) function $F(\theta)$ over a parameter set θ.

e.g. $\theta = (d, t, v)$

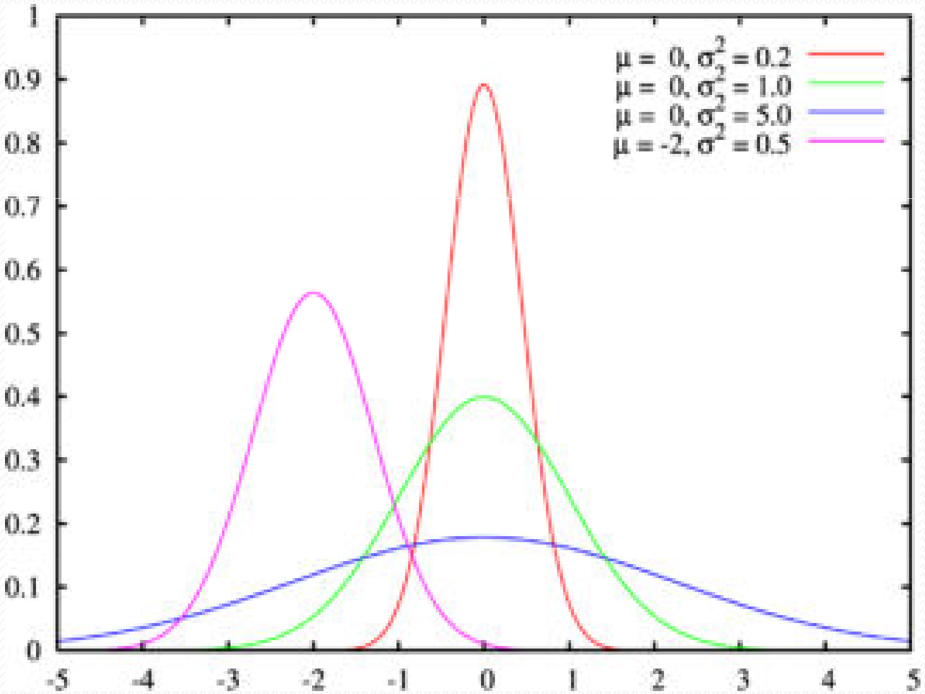
This model can be established by getting consecutive sensing readings (system states) when a mobile sensor node moves.

2. Distance Prediction Model

(1)We extend the Gaussian distribution to two variants multidimensional distribution.(**trust interval** and **RSSI**)

Gaussian distribution

$$X \sim N(\mu, \sigma^2), \Longrightarrow f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

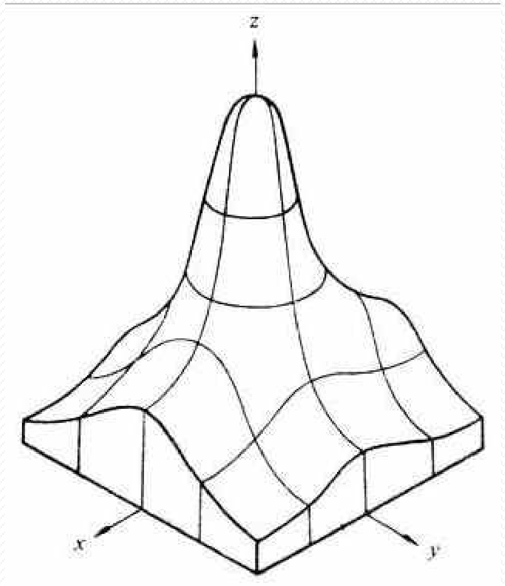


Source:
http://en.wikipedia.org/wiki/Normal_distribution

2-dimentioanl Gaussian distribution

$$\varphi(x,y)=\frac{1}{2\pi\sigma_x\sigma_y\sqrt{1-r^2}}e^{-\frac{1}{2(1-r^2)}\left[\frac{(x-\mu_x)^2}{\sigma_x^2}-\frac{2r(x-\mu_x)(y-\mu_y)}{\sigma_x\sigma_y}+\frac{(y-\mu_y)^2}{\sigma_y^2}\right]}$$

$$(X,Y)\sim N(\mu_1,\sigma_1^2;\mu_2,\sigma_2^2;\ )$$



二维正态分布的密度函数

Gradrive Model Details

(2)Assume the trust interval set by a rescue team is independent of the RSSI received.

(3) Without loss of generality, it is assumed that the predicted distance d is disproportional to RSSI, that can be expressed as **$d = r_1/RSSI + r_2$**, where r_1 and r_2 are two adaptive parameters that can be determined before the searching process.

(4) We then use historical data or experience data to construct the models, providing r_1 and r_2 at each RSSI value appropriately.

Gradrive Model Details

(5) Besides offering the predicted distance, a probability model associated the d is also constructed to provide confidence of the prediction, e.g. given a predicted distance of 2 feet, the confidence for this prediction is 95%.

(6) One distribution of the distance d against the confidence P over one RSSI is a Gaussian distribution. Suppose that rescue team have set a trust interval of Ti, given the distribution of distance over one RSSI, we can get the points di that satisfied Ti.

Gradrive Model Details

3.Signal Strength Distribution Prediction Model

(1)Refine the RSSI distribution Model,which can then be used to navigate the mobile sensor network toward the target at a shortest path.

(2)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) considering d and p's distribution are independent.

Gradrive Model Details

(3)do the Tylor expansion on function F,

Get: $F(d, p) = f(d_0, d_1, d_2 \ldots)f(p)$, where di is the function of distance variable d.

$d_0 = c_0$

$d_1 = 1/(d + c_1)$

$d_2 = 1/(d^2 + c_2)$, where c_0, c_1, c_2 are constants used to avoid singularity when $d = 0$.

$F = D \cdot A \cdot p$ where $A = [a_0, a_1, a_2]$

If enough sensing samplings are provided, we can apply Least Square Fitting to estimate the parameters A.

Least Square Fitting

$$y_m(t_1,\ldots,t_q;x_0,x_1,\ldots,x_q)=x_0+x_1t_1+\cdots+x_qt_q$$

$$\begin{gathered}
x_0+x_1t_{11}+\cdots+x_jt_{1j}+\cdots+x_qt_{1q}=y_1\\
x_0+x_1t_{21}+\cdots+x_jt_{2j}+\cdots+x_qt_{2q}=y_2\\
\vdots\\
x_0+x_1t_{i1}+\cdots+x_jt_{ij}+\cdots+x_qt_{iq}=y_i\\
\vdots\\
x_0+x_1t_{n1}+\cdots+x_jt_{nj}+\cdots+x_qt_{nq}=y_n
\end{gathered}$$

$$\begin{pmatrix}1 & t_{11} & \cdots & t_{1j}\cdots & t_{1q}\\ 1 & t_{21} & \cdots & t_{2j}\cdots & t_{2q}\\ \vdots & & & & \\ 1 & t_{i1} & \cdots & t_{ij}\cdots & t_{iq}\\ \vdots & & & & \\ 1 & t_{n1} & \cdots & t_{nj}\cdots & t_{nq}\end{pmatrix}\cdot\begin{pmatrix}x_0\\ x_1\\ x_2\\ \vdots\\ x_j\\ \vdots\\ x_q\end{pmatrix}=\begin{pmatrix}y_1\\ y_2\\ \vdots\\ y_i\\ \vdots\\ y_n\end{pmatrix}$$

$$Ax = b$$

$$\min_x \|Ax-b\|_2$$

Gradrive Model Details

- Shortcoming:

  Computation of the matrix does cost a large amount of the wireless nodes' energy.

- Solution:

  Send data back to a base station, where stronger computation ability and energy are normally not limitations. Then the base station send the global information back to each sensor node.

TARGET LOCALIZATION USING THE COLLABORATIVE PREDICTION MODEL

- Each mobile sensor nodes can infer the position of target (x, y) and the associated confidence value p.
- Example:

The predicted target location provided by sensor nodes n_1, n_2, …, nk, are (x_1, y_1), (x_2, y_2), …, (xk, yk) associated with probability value p_1, p_2, …pk.

$$X = \frac{\sum_{i=1}^{k} p_k x_k}{\sum_{i=1}^{k} p_k} \quad Y = \frac{\sum_{i=1}^{k} p_k y_k}{\sum_{i=1}^{k} p_k}$$

Collaborative Navigation and Prediction Protocol

- (1) Sensor nodes enter an intended region with certain moving speeds, moving directions and trust intervals.
- (2) The mobile sensor nodes continue to detect the RSSI in its sensing range.
- (3) The sensor nodes estimate their distance to the target position according to the sensing RSSI, randomly pick one prediction within its trust interval.
- (4)Sent target location info forward to base station.
- (5) After the global picture in some confidence level is finished, every node change the direction according to the map.

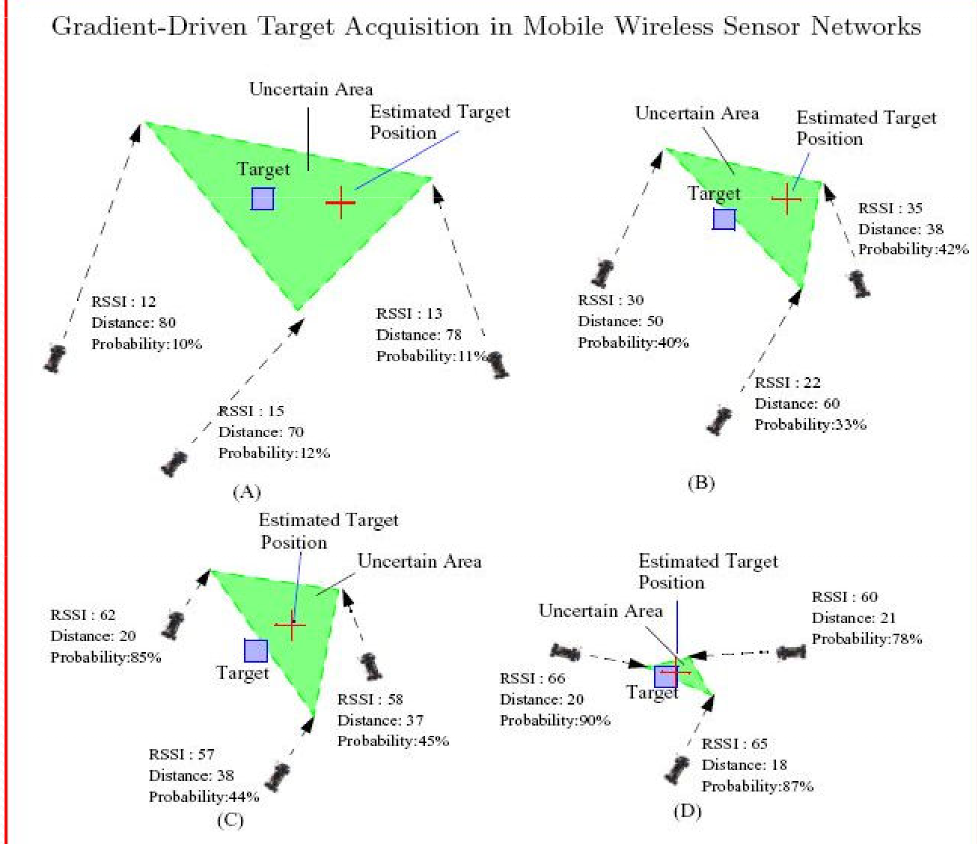


Fig. 2. Collaborative Prediction Scheme of GraDrive

Default Navigation Plan when Global Prediction Unavailable

Given its current sensing reading, it compares with previous readings stored in memory at each motion step. After getting a smaller sensing reading, it rotates 90 degrees clockwise. The reason for that is that the target position is most likely located perpendicularly to its previous moving direction.

EXPERIMENTS AND SIMULATION

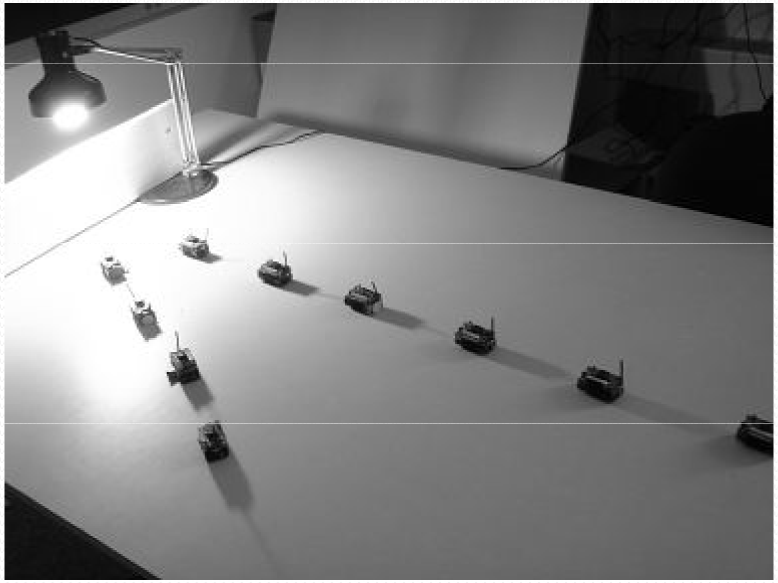
Light signal strength : RSSI

One laptop with motherboard: Base Station

A lamp: Target

A 200×200 m_2 area : an unknown space with a target located at the center

Initially, the mobile nodes are located at the edges of the area. The initial direction is randomly picked by each mobile sensor node. If some sensor nodes move outside the simulation region, they bounce their moving direction back into simulation area.



EXPERIMENTS AND SIMULATION

Under simulation, each mobile sensor node moves at a constant speed in integer multiples of 1 m/s. After each time unit (1 second in our case), a node determines their next moving direction according to our algorithm.

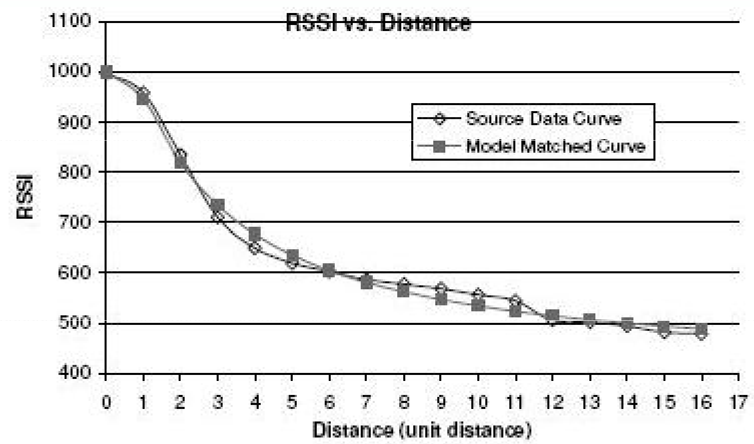


Fig. 4. The predicted model with real sensing data

Compare aganst Random Way Point Model

Without a global distribution calculation mode :

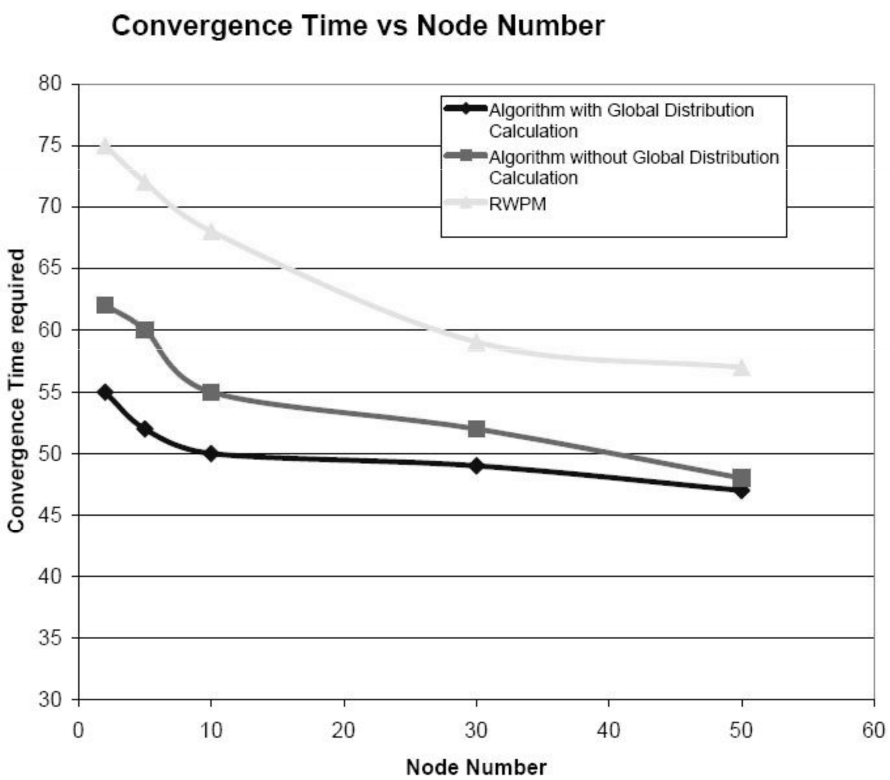
30% faster estimation than

the random way method

With a global distribution

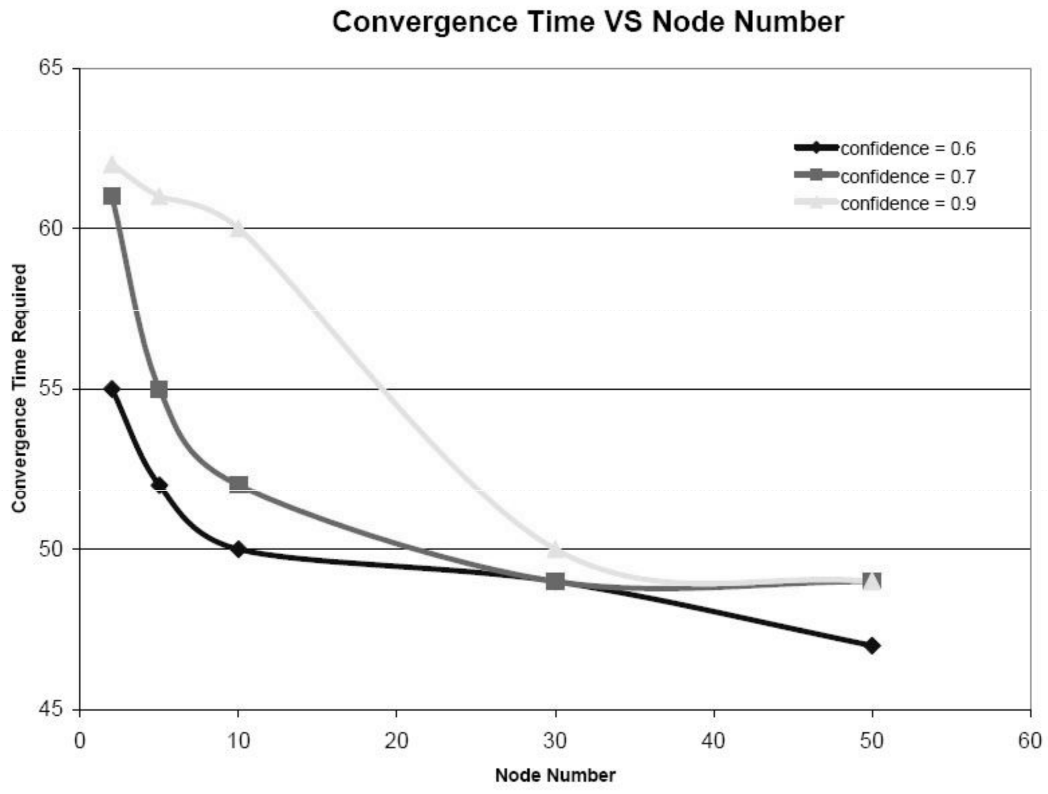
calculation mode :

Even faster



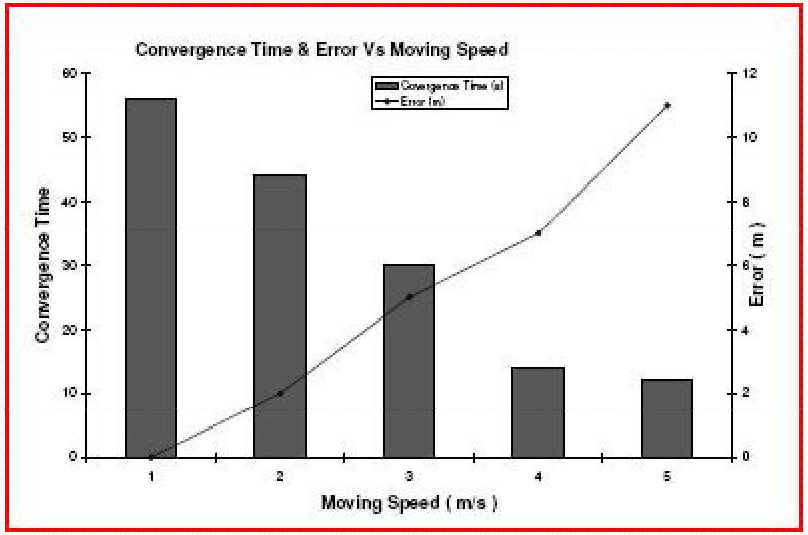
Impact of the Confidence p

It is reasonable to Choose a relative high confidence level e.g. 80% in order to balance accuracy and Time cost.



Impact of the Target Speed

To protect against inaccuracies in the prediction model of mobile sensor nodes, a user must set a limit for moving speed of sensor nodes.



CONCLUSION

Does not require any known map to determine the positions of potential targets.

The proposed gradient driven algorithm leads to a 40% reduction in time compared to that of a random working model.

The relationship between sensor density and convergence time can be used as a reference of consideration for doing planning of such a mobile sensor network.

Even though the computation power could be large, the error of the predicted target position can reach to almost zero and in a short time (about only 47sec).

Remaining Problem

As future work, we would like to implement our algorithm on off-the-shelf hardware platforms. We would also need to design a speed self-adjusting algorithm so that the sensor node has the ability to trade off performance and cost.

Applications

- Tracking, differentiated surveillance, and environment monitoring

- Search and rescue missions in which the background environments are inaccessible to humans.

Example

Thank you for your attention!

Questions?