Development of Novel Computational Algorithms for Localization in Wireless Sensor Networks through Incorporation of Dempster-Shafer Evidence Theory

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Overview

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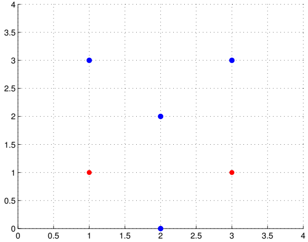
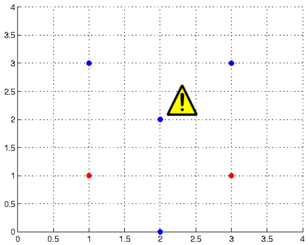
Wireless Sensor Network



- Collection of small, interchangeable low-power devices that monitor sensory data
- Node responds to event and sends alert signal
- Anchor node reads measurements from all sensor nodes
- Data from anchor nodes are processed to locate the node

Wireless Sensor Network



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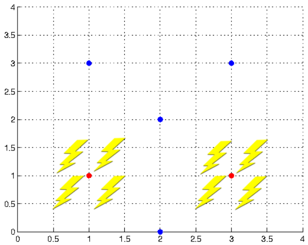

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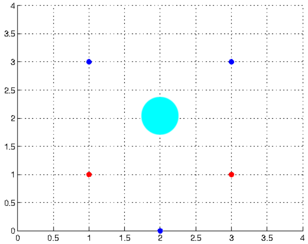

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Problem Statement

Goals and Objectives of this Research

To develop new methods for finding a Node's location in a Wireless Sensor Network with both High Accuracy and Low Computational Cost

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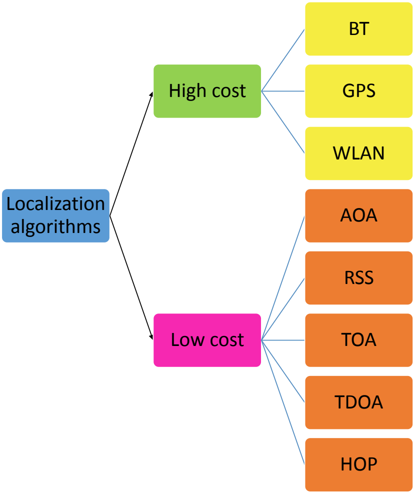
Established Localization Techniques



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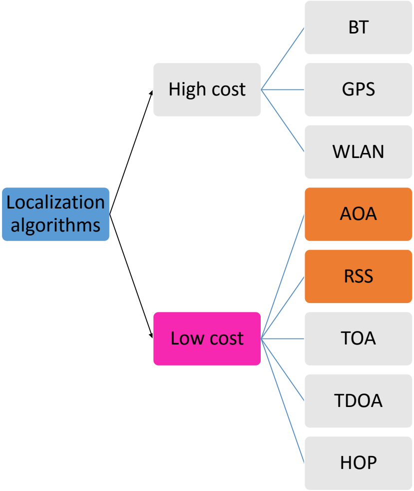
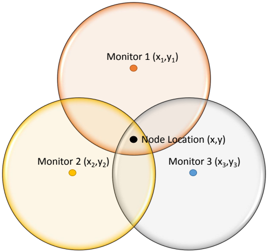
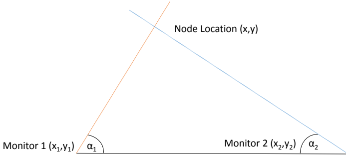


Received Signal Strength (RSS)



- Defined as measured power or square of signal strength
- Most vital property: RSS is inversely proportional to distance
- Estimation done by trilateration

Angle of Arrival (AOA)



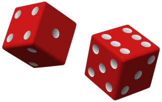
- Measures angles at 2+ receivers
- Estimation done through triangulation
- Based on TDOA measurements

Other Localization Techniques

Technique	Overview	Advantages	Disadvantages
Genetic Algorithm (GA)	Evolutionary population of candidate solutions	Ideal for large-scale search problems	Premature convergence
Particle Swarm Optimization (PSO)	Based on particles and movements	Ideal for problems with real values	Expensive computational runtime

Table: Summary of global, biologically inspired localization techniques.

Overview of DS Theory



- Divergence from Bayesian Probability
- Based on concept of ignorance
- Bayesian probability combines internal factors
- DS Theory uses external factors

Example: Broken Chair

Component	Failure Probability
Wheels	60% chance of breaking
Back	20% chance of falling apart
Arm Rests	40% chance of falling off

Table: Failure analysis of each chair component

Probability of Total Failure

$.6 \times .4 \times .2 = .048$ or 4.8%

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Example: Broken Chair

Expert	Lower Bound	Upper Bound	Confidence
A	11	18	.4
B	14	21	.4
C	10	20	.2

Table: Failure analysis by three experts

- Expected Value Range of 100% Failure: 12-19.6 Days
- Most Plausible Time of 100% Failure: 14 Days
- Most Believable Time of 100% Failure: 21 Days

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Applications of and Motivations for DS Theory

(a) Failure Analysis

(b) Robot Sensor Fusion

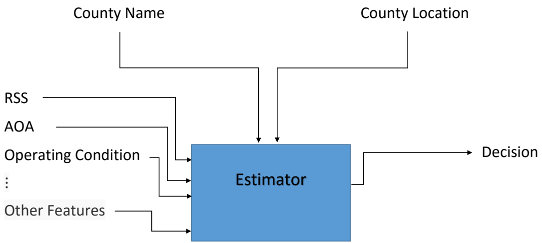
(c) GPS/INS Data Fusion

(d) Wireless Sensor Networks

- No need to train data
- Fast and computationally efficient

First Proposed Algorithm

- Does the set of measurements belong to the county?



DS Theory: Mathematical Foundation

Suppose that:

- Finite set of all possible mutually exclusive values are denoted as Frame of Discernment, Θ
- $A_1, \ldots, A_n$ denote all possible sets within power set 2^Θ

Theorem (Basic Probability Assignment (BPA) m)

$$m : 2^\Theta \rightarrow [0,1], \sum_{i=1}^{n} m(A_i) = 1, m(\emptyset) = 0$$

Theorem (Aggregation of m_1 and m_2)

$$[m_1 \oplus m_2] = \frac{\sum_{A \cap B = y} m_1(A) m_2(B)}{1 - \sum_{A \cap B = y} m_1(A) m_2(B)}$$

Belief and Plausibility

- Let $m(A_i)$ denote BPA mass function for set A_i
- Belief represents best case scenario in frame of discernment
- Plausibility represents worst case scenario

Theorem (Belief of B)

$Bel(B) = \sum_{A_i \subset B} m(A_i)$

Theorem (Plausibility of B)

$Pl(B) = 1 - \sum_{A_i \cap B = \emptyset} m(A_i)$

Linear Representation

- BPA consists of lower bound, upper bound, and confidence probability

$$m = \begin{bmatrix} \underline{x} & \bar{x} & \mu \end{bmatrix} \tag{1}$$

- For all BPAs, expected value can be calculated as

$$Val_{Ex} = \sum_{BPAs} \begin{bmatrix} \mu\underline{x} & \mu\bar{x} \end{bmatrix} \tag{2}$$

- An aggregate BPA can be expressed in matrix form as

$$m = \begin{bmatrix} m_1 \\ m_2 \\ \vdots \\ m_n \end{bmatrix} = \begin{bmatrix} \underline{x}_1 & \bar{x}_1 & \mu_1 \\ \underline{x}_2 & \bar{x}_2 & \mu_2 \\ \vdots & \vdots & \vdots \\ \underline{x}_n & \bar{x}_n & \mu_n \end{bmatrix} \tag{3}$$

Data Fusion

- Measurement types (features) consist of RSS, AOA, and operating condition (standby mode)

$$\lambda = \begin{bmatrix}\lambda_{RSS} & \lambda_{AOA} & \lambda_{SB}\end{bmatrix}^T \tag{4}$$

where

$$\lambda_{RSS} = \begin{bmatrix} m_{1,RSS} \\ m_{2,RSS} \\ \vdots \\ m_{n,RSS} \end{bmatrix}, \lambda_{AOA} = \begin{bmatrix} m_{1,AOA} \\ m_{2,AOA} \\ \vdots \\ m_{n,SB} \end{bmatrix}, \lambda_{SB} = \begin{bmatrix} m_{1,SB} \\ m_{2,SB} \\ \vdots \\ m_{n,SB} \end{bmatrix} \tag{5}$$

$$m_i = \begin{bmatrix} d_{min} & d_{max} & 1 \end{bmatrix}, i = 1, 2, \ldots, n \tag{6}$$

Measurement Types I

- RSS $\propto \frac{1}{d^a}$ in general context; $a = 2$ in free space

$$RSS = \frac{1}{d^2} \tag{7}$$

- AOA is determined as

$$AOA = \begin{cases} tan^{-1}(\frac{y_n - y_m}{x_n - x_m}) & \text{if } y_n > y_m \text{ and } x_n > x_m \\ tan^{-1}(\frac{y_n - y_m}{x_n - x_m}) + 180 & \text{if } y_n \neq y_m \text{ and } x_n < x_m \\ tan^{-1}(\frac{y_n - y_m}{x_n - x_m}) + 360 & \text{if } y_n < y_m \text{ and } x_n > x_m \end{cases} \tag{8}$$

Measurement Types II

- Standby is distance measurement of node in low power (standby) mode from standby node
- Distance is obtained by back calculation of RSS

$$SB = \sqrt{\frac{1}{RSS_{sb}}} \tag{9}$$

$$SB = \sqrt{(x_{sb}^2 - x_n^2) + (y_{sb}^2 - y_n^2)} \tag{10}$$

Overview of First Algorithm

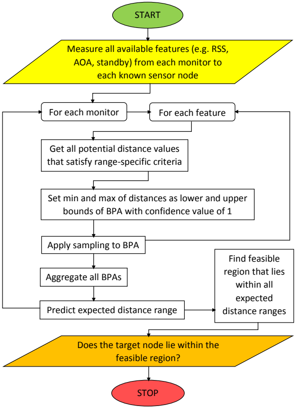
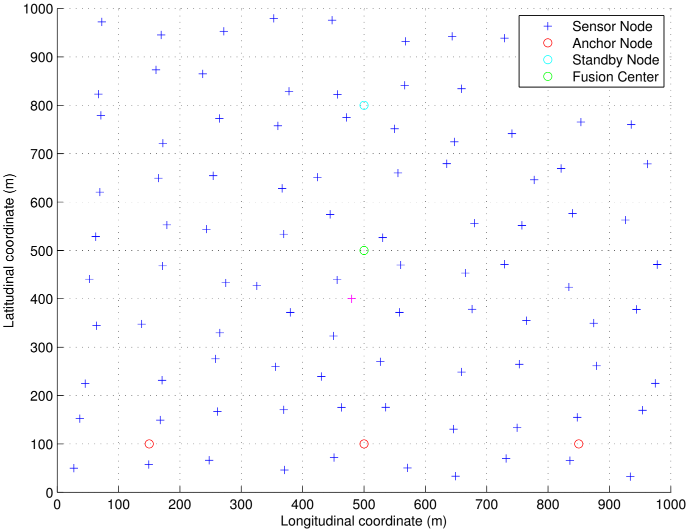


Figure: Flowchart of DS localization algorithm.

Algorithm in Execution



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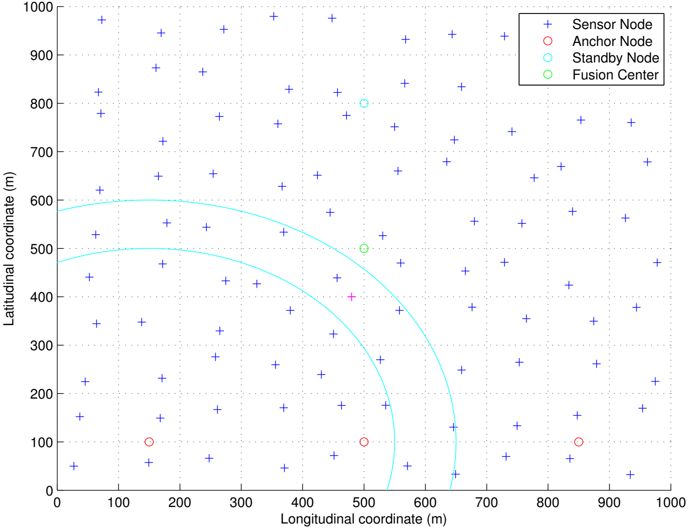

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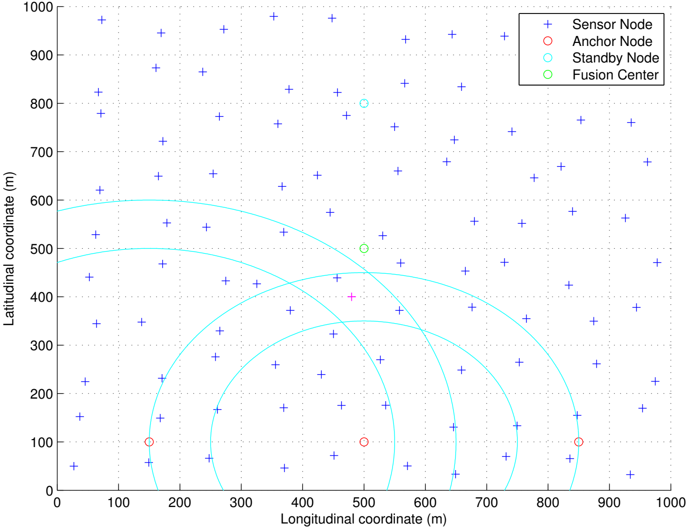

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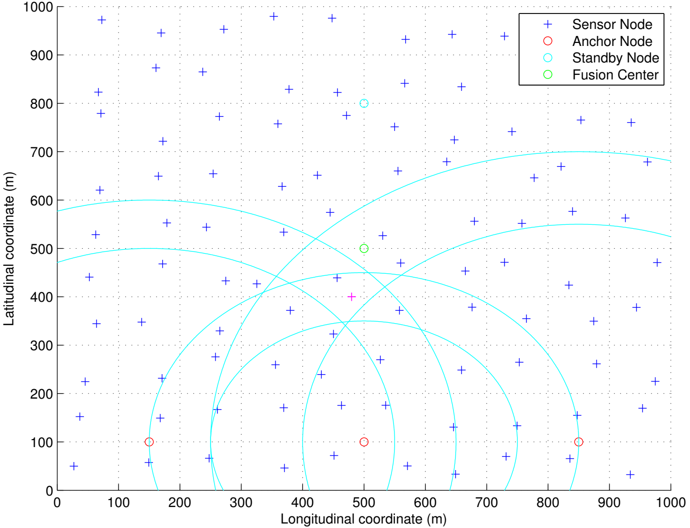

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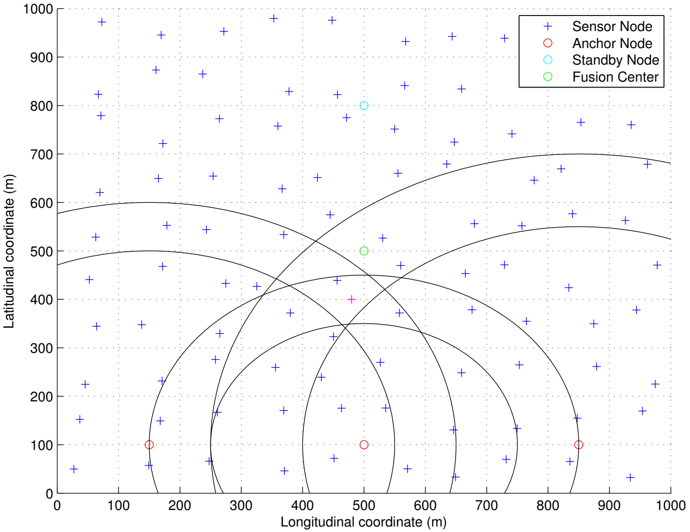


Experimental Setup I

- Software: MATLAB with IPP Toolbox
- Hardware: Quad Core CPU and 8.0 GB RAM
- 10 Independent Trials for each feature combination
- 100 sensor nodes, 3 anchor nodes, standby node, fusion center

Experimental Setup II

- One-to-one mapping between sensor nodes and counties
- RSS range of 20, AOA range of 100, no standby range
- Tested for RSS+SB, RSS+AOA, and RSS+AOA+SB
- 10 samples per BPA as inverse normalized distribution
- Zero noise factor and zero anchor node positioning error assumed

Accuracy Calculation I

- A decision is made for every combination of county and measurement set
- Decision is either yes (1) or no (0)

$$\begin{bmatrix} dec_{11} & dec_{12} & \dots & dec_{1n} \\ dec_{21} & dec_{22} & \dots & dec_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ dec_{n1} & dec_{n2} & \dots & dec_{nn} \end{bmatrix} \tag{11}$$

Accuracy Calculation II

- The results are compared against the ideal decision matrix

$$\begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 \end{bmatrix} \tag{12}$$

- Accuracy is calculated by

$$Accuracy = 100 * \frac{cells_{matching}}{cells_{total}} \tag{13}$$

Internal Results

Table: Simulation results.

Feature Description	Test Accuracy (%)	Runtime (μs)
RSS, SB	79.97	12736.30
RSS, AOA	78.41	12731.71
RSS, AOA, SB	87.36	12731.49

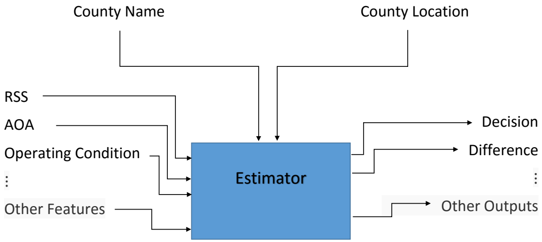
External Results

Table: Comparison of accuracy among different localization techniques.

Algorithm	PSO	WSLA	WSRA	MLE	DS1
Accuracy (%)	71	90	92	93	87
Runtime (μs)	114570	7800	9700	NR	12733

Second Proposed Algorithm

- Does the set of measurements belong to the county?
- Which county most closely matches the set of measurements?



Formation of Belief I

- Recall that an aggregate BPA can be expressed as

$$m = \begin{bmatrix} m_1^u \\ m_2^u \\ \vdots \\ m_n^u \end{bmatrix} = \begin{bmatrix} \underline{x}_1^u & \bar{x}_1^u & \mu_1^u \\ \underline{x}_2^u & \bar{x}_2^u & \mu_2^u \\ \vdots & \vdots & \vdots \\ \underline{x}_n^u & \bar{x}_n^u & \mu_n^u \end{bmatrix} \tag{14}$$

- Superscript u denotes that $\bar{x}_1^u < \bar{x}_2^u < \cdots < \bar{x}_n^u$

Formation of Belief II

- Then belief can be formed as

$$Bel = \begin{bmatrix} \bar{x}_1^u & \mu_{1,new}^u \\ \bar{x}_2^u & \mu_{2,new}^u \\ \vdots & \vdots \\ \bar{x}_n^u & \mu_{n,new}^u \end{bmatrix} \tag{15}$$

where

$$\mu_{1,new}^u = \mu_1^u \tag{16}$$

$$\mu_{2,new}^u = \mu_2^l + \mu_{1,new}^u \tag{17}$$

$$\mu_{n,new}^u = \mu_n^u + \mu_{(n-1),new}^u \tag{18}$$

Formation of Plausibility I

- Now suppose m is rearranged and $m_1^u, m_2^u, \ldots, m_n^u$ are renamed such that

$$m = \begin{bmatrix} m_1^l \\ m_2^l \\ \vdots \\ m_n^l \end{bmatrix} = \begin{bmatrix} \underline{x}_1^l & \bar{x}_1^l & \mu_1^l \\ \underline{x}_2^l & \bar{x}_2^l & \mu_2^l \\ \vdots & \vdots & \vdots \\ \underline{x}_n^l & \bar{x}_n^l & \mu_n^l \end{bmatrix} \tag{19}$$

- Superscript l denotes that $\underline{x}_1^u < \underline{x}_2^u < \cdots < \underline{x}_n^u$

Formation of Plausibility II

- Then plausibility can be formed as

$$Pl = \begin{bmatrix} \underline{x}_1^l & \mu_{1,new}^l \\ \underline{x}_2^l & \mu_{2,new}^l \\ \vdots & \vdots \\ \underline{x}_n^l & \mu_{n,new}^l \end{bmatrix} \tag{20}$$

where

$$\mu_{1,new}^l = \mu_1^l \tag{21}$$

$$\mu_{2,new}^l = \mu_2^l + \mu_{1,new}^l \tag{22}$$

$$\mu_{n,new}^l = \mu_n^l + \mu_{(n-1),new}^l \tag{23}$$

Overview of Second Algorithm

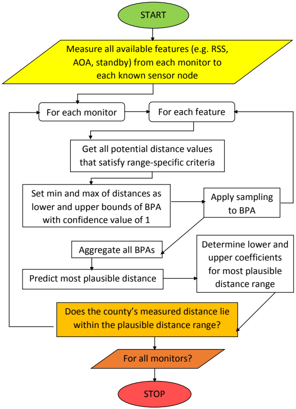
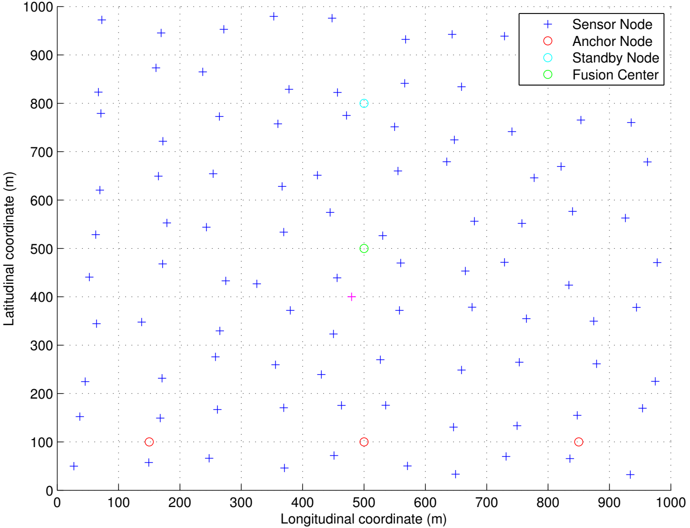


Figure: Flowchart of DS localization algorithm

Algorithm in Execution



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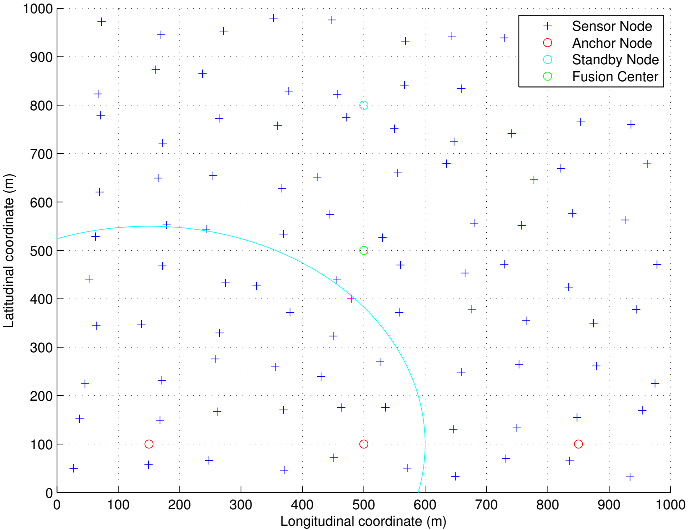

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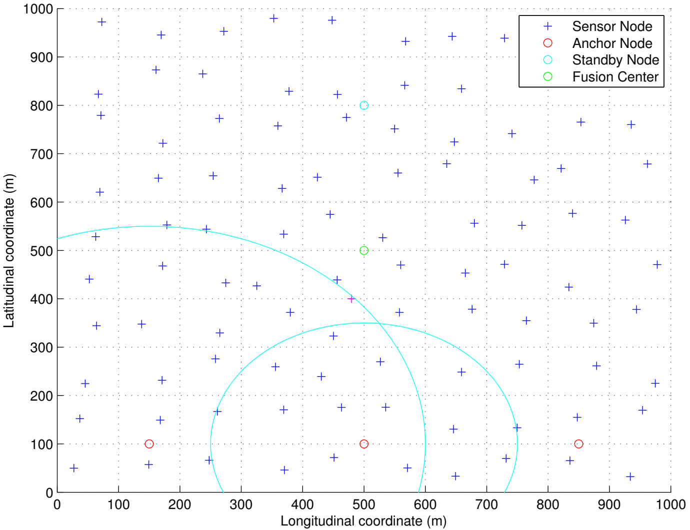

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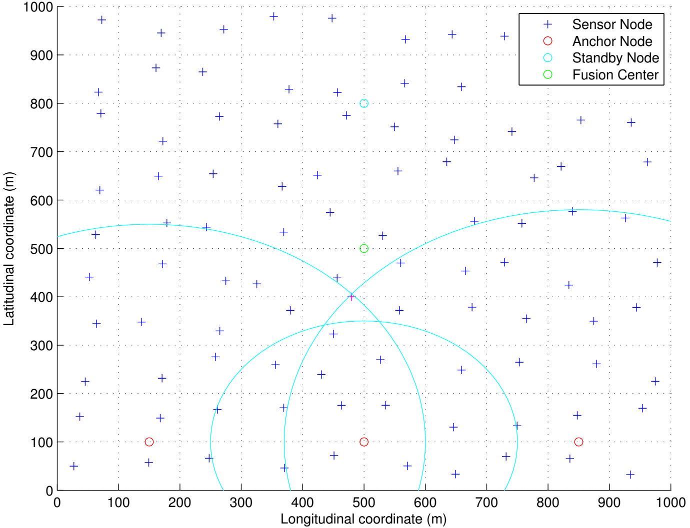

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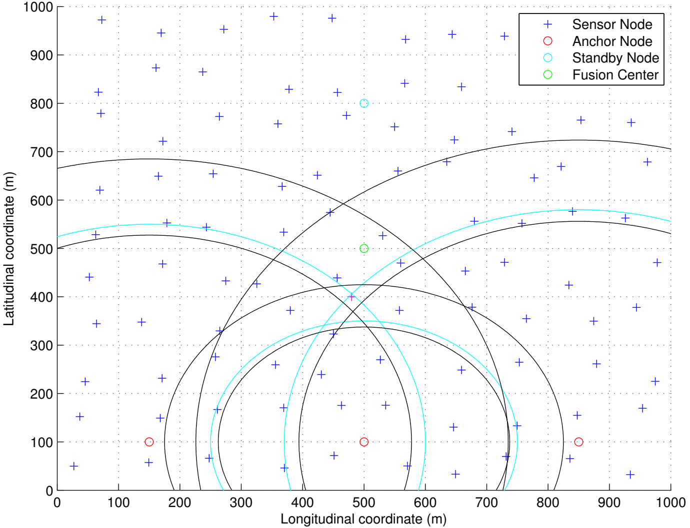

Determination of Optimal Distance Range

- Need upper and lower weights to determine distance range that yields most optimal accuracy
- Training is one-time occurrence not essential to DS Theory
- Candidate upper bounds are 1.1, 1.3, 1.5, 1.7, and 1.9
- Candidate lower bounds are 0.2, 0.45, 0.7, and 0.95
- Iterative training consists of 30 independent trials per feature set

Changes in Experimental Setup

- Tested for both 2 and 3 active anchor nodes
- AOA range of .002
- Inverses of feature values compared with range values
- Tested for every feature combination in which RSS is active
- (Actual distance - predicted distance) of <-1.5 not considered

Three Types of Accuracy Calculation

- **Full Accuracy**
  Based on all possible combinations of measurement sets and counties
- **Short Accuracy**
  Based only on all possible correct combinations
- **Matching Accuracy**
  Based on county matches for all measurement sets

Full Accuracy Calculation

- Decision matrix

$$\begin{bmatrix} dec_{11} & dec_{12} & \dots & dec_{1n} \\ dec_{21} & dec_{22} & \dots & dec_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ dec_{n1} & dec_{n2} & \dots & dec_{nn} \end{bmatrix} \tag{24}$$

is compared against ideal matrix

$$\begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 \end{bmatrix} \tag{25}$$

for all combinations of measurement sets and counties

Short Accuracy Calculation

- Decision matrix based only on correct combinations

$$\begin{bmatrix} dec_1 & dec_2 & \dots & dec_n \end{bmatrix} \tag{26}$$

- Ideal matrix

$$\begin{bmatrix} 1 & 1 & \dots & 1 \end{bmatrix} \tag{27}$$

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Matching Accuracy Calculation

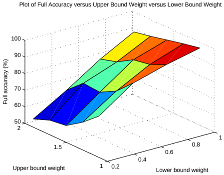
- Matching matrix based on all possible feature sets

$$\begin{bmatrix} match_1 & match_2 & \dots & match_n \end{bmatrix} \tag{28}$$

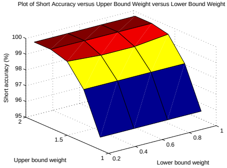
- Ideal matrix

$$\begin{bmatrix} 1 & 2 & \dots & n \end{bmatrix} \tag{29}$$

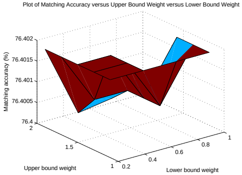
Accuracy Results under Iterative Weight Training



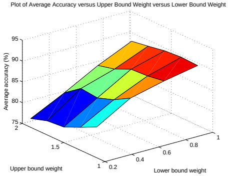
(a) Full Accuracy



(b) Short Accuracy



(c) Matching Accuracy



(d) Average Accuracy

Internal Results: Accuracy

Table: Simulation results for two-monitor and three-monitor WSNs.

Accuracy	Full (%)		Short (%)		Match (%)		Average (%)	
Monitors	2	3	2	3	2	3	2	3
RSS	97.04	97.49	97.20	98.50	56.17	66.64	83.47	87.54
RSS, SB	97.00	97.43	100.0	100.0	94.58	96.07	97.19	97.83
RSS, AOA	97.03	97.47	98.13	98.97	57.81	67.29	84.33	87.92
RSS, AOA, SB	97.01	97.44	100.0	100.0	92.52	94.21	96.51	97.22

Internal Results: Runtime

Table: Runtime results for two-monitor and three-monitor WSNs.

Runtime (ms)	2 Monitors	3 Monitors
Total	787478.00	1375261.00
Per Feature Set	196869.00	343815.20
Per Iteration	17.20	30.03
Per Node	0.160	0.281

External Results

Table: Comparison of accuracy among different localization techniques.

Algorithm	PSO	WSLA	WSRA	MLE	DS1	DS2
Accuracy (%)	71	90	92	93	87	97
Runtime (μs)	114570	7800	9700	NR	12733	281

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Publications

Colin Elkin, Rajika Kumarasiri, and Vijay Devabhaktuni, "A novel approach to localization in wireless sensor networks using Dempster-Shafer evidence theory," *Expert Systems with Applications* (Under review).

Conclusions

- Dempster-Shafer Evidence Theory was introduced for the first time to the area of WSN localization
- Expected value function generates good accuracy but with high computational cost
- Plausibility function generates great accuracy at low computational cost
- Variety of applications in time-critical WSN localization will be greatly enhanced with these novel algorithms

Future Work

- Fusion of DS Theory with Support Vector Machines
- DS Theory as Meta-Learning Component for Data Mining
- Enhance Training of Upper and Lower Bound Coefficients

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- Dr. Vijay Devabhaktuni
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- All attendees here today
- Rajika Kumarasiri, Hem Regmi, and Arushi Gupta
- Colleagues at NE 2033 & 2042
- My family and friends, both near and far

Thank you

Any Questions?