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

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Overview

Wireless Sensor Network

- Collection of small, interchangeable, disposable 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 sending the alert

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Problem Statement

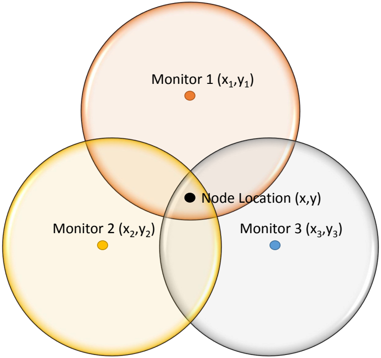
Objectives and Goals of This Research

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

Applications and Challenges

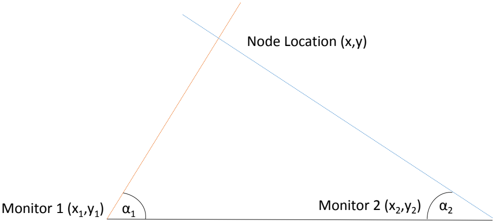
Established Localization Techniques

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
D	14	21	.4
W	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
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Proposed Algorithm

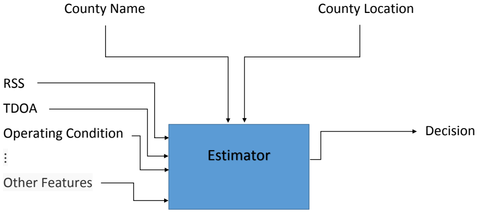


Figure: First proposed classifier.

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

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

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

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

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

Measurement Types

$$RSS = \frac{1}{d^2} \tag{4}$$

$$AOA = \begin{cases} tan^{-1}(\frac{y_n - y_m}{x_n - x_m}) & \text{if } y_n > y_m \text{ and } x_n > x_m \\ tan^{-1}(\frac{y_n - y_m}{x_n - x_m}) + 180 & \text{if } y_n \neq y_m \text{ and } x_n < x_m \\ tan^{-1}(\frac{y_n - y_m}{x_n - x_m}) + 360 & \text{if } y_n < y_m \text{ and } x_n > x_m \end{cases} \tag{5}$$

$$SB = \sqrt{(x_{sb}^2 - x_n^2) + (y_{sb}^2 - y_n^2)} \tag{6}$$

Data Fusion

$$\lambda = \begin{bmatrix}\lambda_{RSS} & \lambda_{AOA} & \lambda_{SB}\end{bmatrix}^T \tag{7}$$

$$\lambda_{RSS} = \begin{bmatrix} m_{1,RSS} \\ m_{2,RSS} \\ \vdots \\ m_{n,RSS} \end{bmatrix}, \lambda_{AOA} = \begin{bmatrix} m_{1,AOA} \\ m_{2,AOA} \\ \vdots \\ m_{n,SB} \end{bmatrix}, \lambda_{SB} = \begin{bmatrix} m_{1,SB} \\ m_{2,SB} \\ \vdots \\ m_{n,SB} \end{bmatrix} \tag{8}$$

$$m_i = \begin{bmatrix} d_{min} & d_{max} & 1 \end{bmatrix} \tag{9}$$

Algorithm

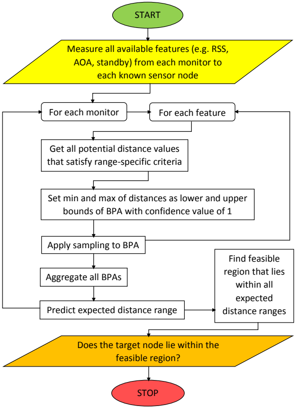


Figure: Flowchart of DS localization algorithm.

Experimental Results

Table: Simulation results.

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

Experimental 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

Proposed Algorithm

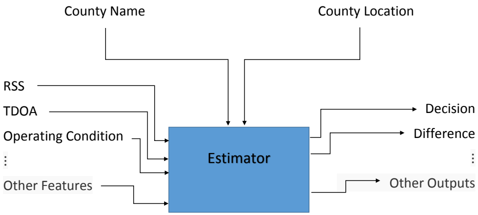


Figure: Second proposed classifier.

Formation of Belief

$$m = \begin{bmatrix} m_1^u \\ m_2^u \\ \vdots \\ m_n^u \end{bmatrix} = \begin{bmatrix} \underline{x}_1^u & \bar{x}_1^u & \mu_1^u \\ \underline{x}_2^u & \bar{x}_2^u & \mu_2^u \\ \vdots & \vdots & \vdots \\ \underline{x}_n^u & \bar{x}_n^u & \mu_n^u \end{bmatrix} \tag{10}$$

$$Bel = \begin{bmatrix} \bar{x}_1^u & \mu_{1,new}^u \\ \bar{x}_2^u & \mu_{2,new}^u \\ \bar{x}_3^u & \mu_{3,new}^u \\ \vdots & \vdots \\ \bar{x}_n^u & \mu_{n,new}^u \end{bmatrix} \tag{11}$$

where

$$\mu_{1,new}^u = \mu_1^u \tag{12}$$

$$\mu_{2,new}^u = \mu_2^l + \mu_{1,new}^u \tag{13}$$

$$\mu_{3,new}^u = \mu_3^u + \mu_{2,new}^u \tag{14}$$

Formation of Plausibility

$$m = \begin{bmatrix} m_1^l \\ m_2^l \\ \vdots \\ m_n^l \end{bmatrix} = \begin{bmatrix} \underline{x}_1^l & \bar{x}_1^l & \mu_1^l \\ \underline{x}_2^l & \bar{x}_2^l & \mu_2^l \\ \vdots & \vdots & \vdots \\ \underline{x}_n^l & \bar{x}_n^l & \mu_n^l \end{bmatrix} \tag{16}$$

$$Pl = \begin{bmatrix} \underline{x}_1^l & \mu_{1,new}^l \\ \underline{x}_2^l & \mu_{2,new}^l \\ \underline{x}_3^l & \mu_{3,new}^l \\ \vdots & \vdots \\ \underline{x}_n^l & \mu_{n,new}^l \end{bmatrix} \tag{17}$$

where

$$\mu_{1,new}^l = \mu_1^l \tag{18}$$

$$\mu_{2,new}^l = \mu_2^l + \mu_{1,new}^l \tag{19}$$

$$\mu_{3,new}^l = \mu_3^l + \mu_{2,new}^l \tag{20}$$

Algorithm

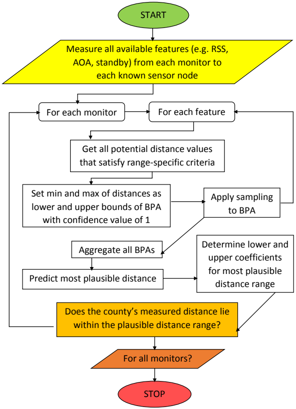
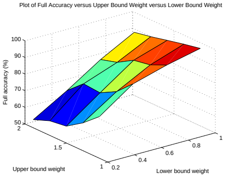
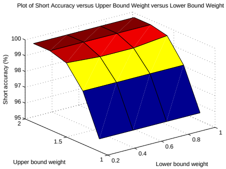


Figure: Flowchart of DS localization algorithm

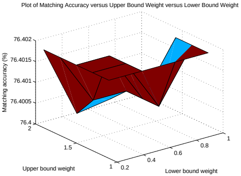
Accuracy Results under Iterative Weight Training



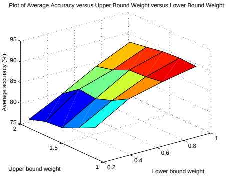
(a) Full Accuracy



(b) Short Accuracy



(c) Matching Accuracy



(d) Average Accuracy

Experimental Results

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

Experimental Results

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

Experimental 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

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

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

Acknowledgements

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- My family and friends, both near and far

Thank you

Any Questions?