Bias Correction in Localization Problem

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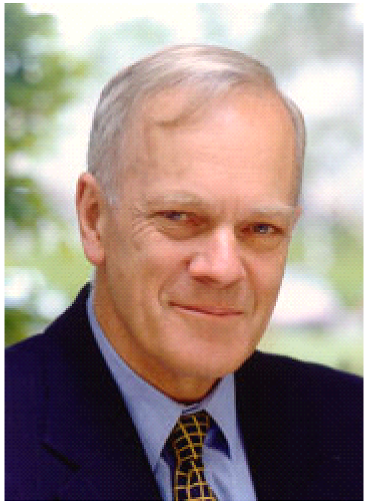

Professor Brian D. O. Anderson

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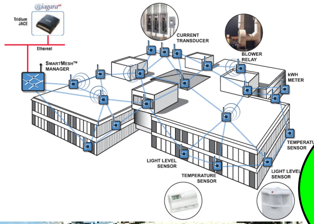
Outline

- Motivation
- Bias in Localization Problem
- Taylor-Jacobian Bias Correction Method
- Performance Evaluation and Simulation
- Conclusion

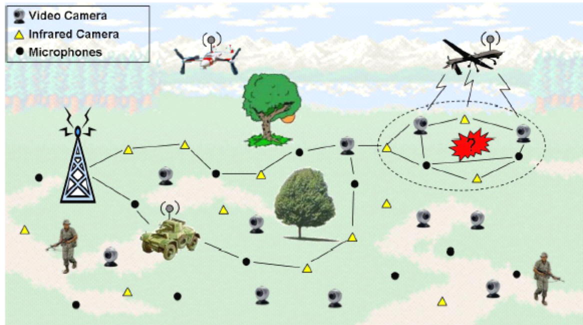
Motivation

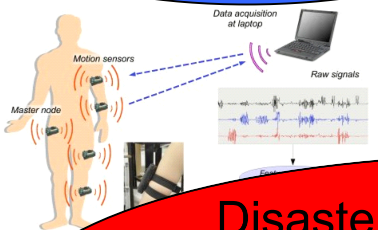


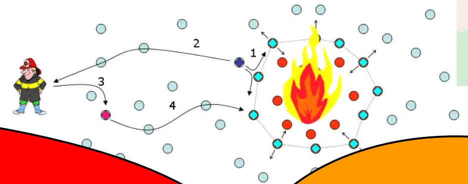

Industry
- *Process control*
- *Automation*
- *Predictive maintenance*

Scientific Research
- *High spatial and temporal density sampling*
- *Habitat monitoring*
- *Event detection*


Health Care
- *Location aware patient monitoring*
- *Patient vital signals*






Disaster Management
- *Event detection (natural disasters – fire, earthquake)*
- *Location awareness (fire fighters looking for survivors)*
- *Emergency response*

Military
- *Battlefield surveillance*
- *Target tracking*

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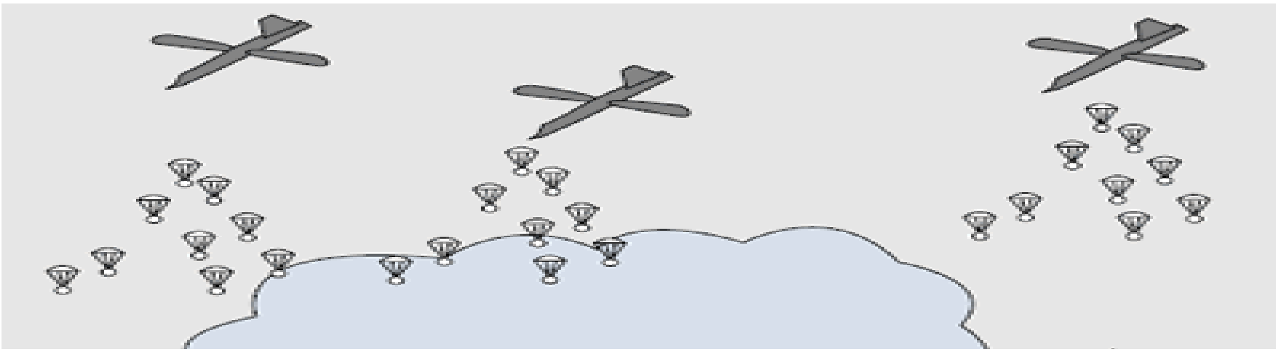
Motivation

- Accurate location of sensors plays a vital role in various network applications



Motivation

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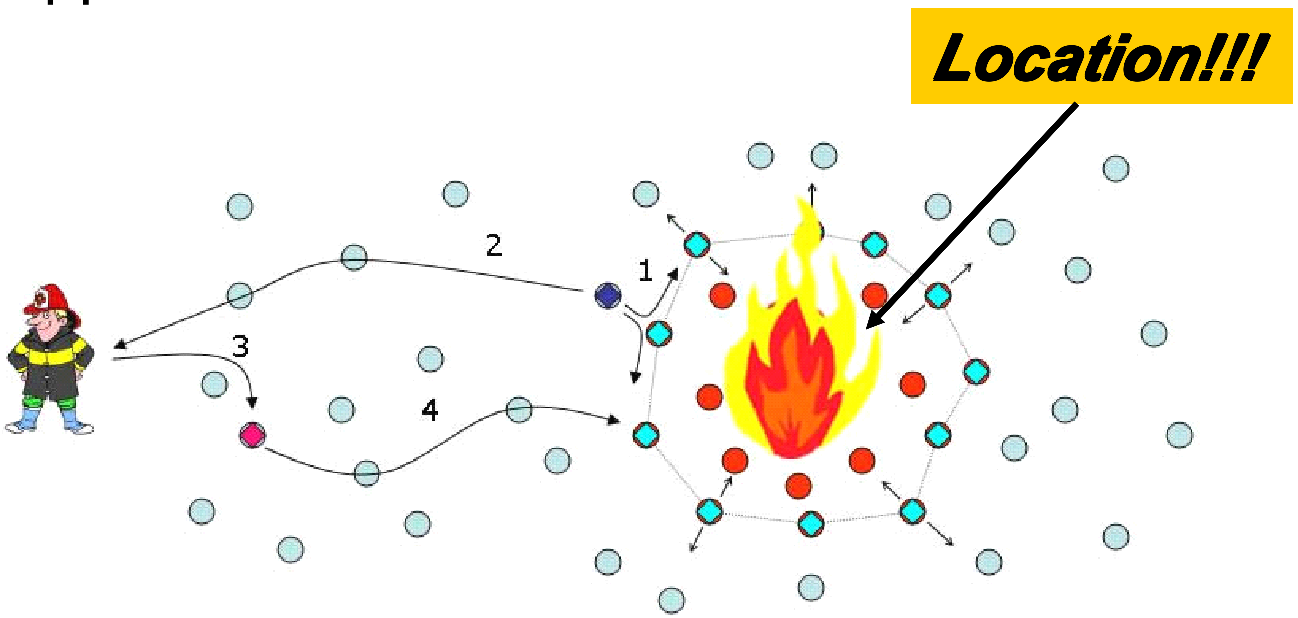

Motivation

- Many self-localization algorithms are proposed
- Generally, localization results are imprecise
    - Environment: noise, non line of sight
    - Hardware: range or angle measuring devices
    - Localization algorithms
- Many enhancement techniques have been proposed to improve the accuracy of localization
    - Geometric Constraints
    - Error Control Mechanisms (Baoqi Huang)
    - **Bias Correction Methods**

Motivation

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    - Error Control Mechanisms
    - **Bias Correction Methods**

Why we choose bias?

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What is Bias

Bias is a term in estimation theory and is defined as the difference between the expected value of a parameter estimate and the true value of the parameter [1].

[1] J. L. Melsa and D. L. Cohn. Decision and Estimation Theory. McGraw-Hill Inc, 1978.

What is Bias

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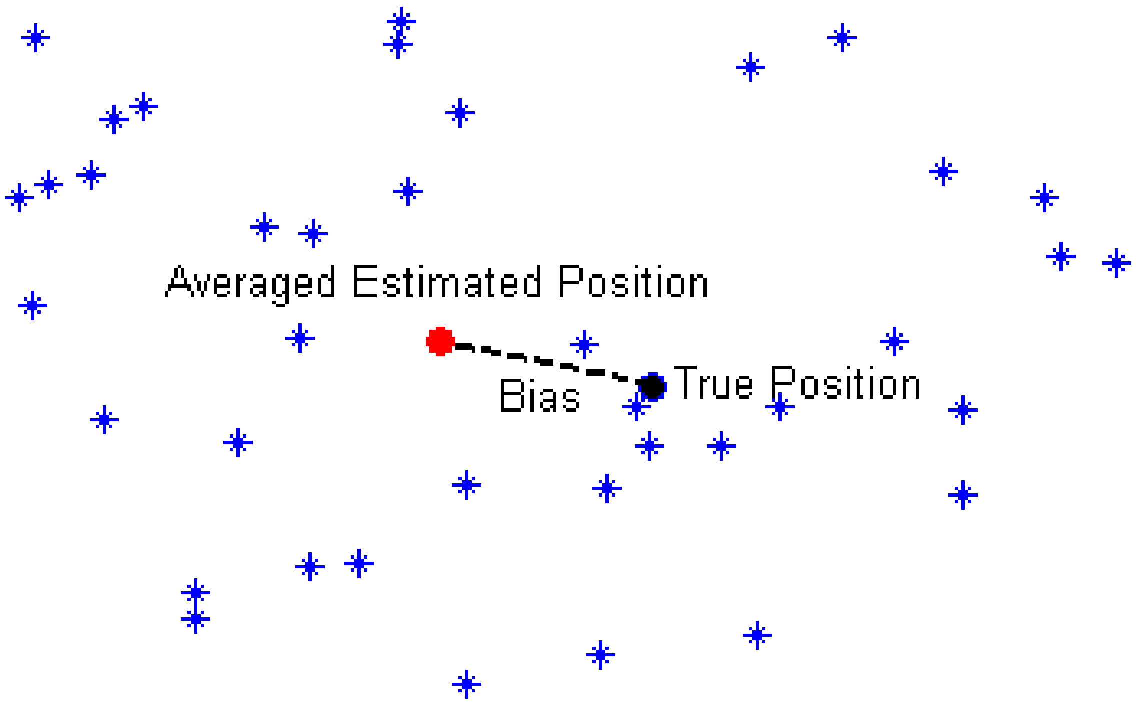

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Bias in Localization Problem

In the noisy situation, we assume $\mathbf{g} = (g_1, g_2, ..., g_n)$ denotes the localization mapping from the measurements to the target position estimates. We have:

$$\tilde{\mathbf{x}} = \mathbf{g}(\Theta + \delta\Theta) = \mathbf{g}(\tilde{\Theta})$$

where $\tilde{\mathbf{x}} = (\tilde{x}_1, \tilde{x}_2, ..., \tilde{x}_n)^T$ denotes the inaccurate estimates of the target location, $\tilde{\Theta} = (\tilde{\theta}_1, \tilde{\theta}_2, ..., \tilde{\theta}_N)$ denotes the noisy measurements and $\delta\Theta = (\delta\theta_1, \delta\theta_2, ..., \delta\theta_N)^T$ denotes the measurement noise.

Bias in Localization Problem

In practice the measurement process will repeated *M* times.

As $M \rightarrow \infty$, we would expect the estimate to go to :

$$E[\tilde{x}_i] = E[g_i(\tilde{\Theta})]$$

Because g_i is nonlinear we have:

$$\begin{aligned} E[\tilde{x}_i] &= E[g_i(\tilde{\Theta})] \\ &\neq g_i(E[\tilde{\Theta}]) \\ &= g_i(\Theta) \\ &= x_i \end{aligned}$$

Therefore the bias appears in the estimation process:

$$Bias_{x_i} = E[\tilde{x}_i] - x_i \qquad i = 1, 2, ..., n$$

Bias in Localization Problem

In practice the measurement process will repeated *M* times.

As $M \to \infty$, we would expect the estimate to go to :

The bias will exist if two conditions are satisfied:

1. the mapping function is nonlinear
2. the measurements are noisy

Becau

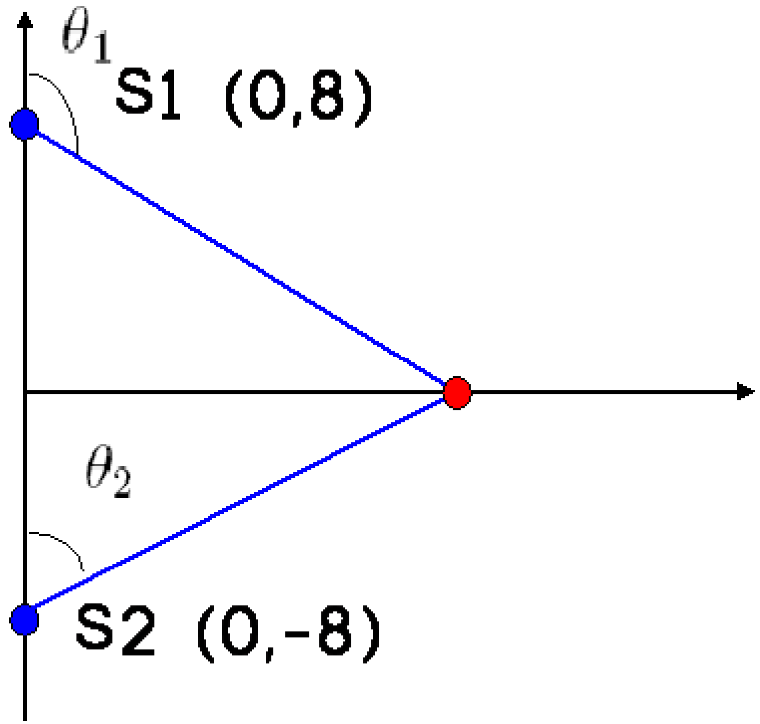
$$= g_i(\Theta)$$
$$= x_i$$

Therefore the bias appears in the estimation process:

$$Bias_{x_i} = E[\tilde{x}_i] - x_i \qquad i = 1, 2, ..., n$$

Significant Bias in Localization Problem

- Two sensors at (0, 8) and (0, -8)
- y value of the target is fixed at 0 while x value changes from 6 to 20
- Measurements are bearing-only
- Different variances used for measurement errors, which are zero mean.



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Significant Bias in Localization Problem

- Table 1 and 2 illustrate the bias of the x component compared to the standard deviation of the error in estimating x with different level of noise

Value of x	6	8	10	12
Percentage (%)	16.48	9.57	6.64	6.17
Value of x	14	16	18	20
Percentage (%)	6.52	7.87	8.51	9.72

TABLE I

THE COMPARISON OF THE BIAS AND THE STANDARD DEVIATION OF X COMPONENT ($\sigma^2 = 1$)

Value of x	6	8	10	12
Percentage (%)	20.92	18.3	14.14	12.5
Value of x	14	16	18	20
Percentage (%)	13.75	15.23	17.24	18.91

TABLE II

THE COMPARISON OF THE BIAS AND THE STANDARD DEVIATION OF X COMPONENT ($\sigma^2 = 2$)

Bias (before removal) can be

a significant fraction of the errors.

Significant Bias in Localization Problem

Normally the two conditions are satisfied easily:

- the mapping function is nonlinear
- the measurements are noisy

The bias can be a significant fraction of the error.

It is worth to analyse and remove the bias in localization.

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Taylor-Jacobian Bias Correction Method

Notations and Assumptions:

1. *n* denotes the number of dimensions of the ambient space
2. *N* denotes the number of obtained measurements
3. $\mathbf{x} = (x_1, x_2, ..., x_n)^T$ denotes the position of the target
4. $\Theta = (\theta_1, \theta_2, ..., \theta_N)^T$ denotes the measurement set
5. $\delta\Theta = (\delta\theta_1, \delta\theta_2, ..., \delta\theta_N)^T$ denotes measurement errors
6. $\mathbf{f} = (f_1, f_2, ..., f_N)^T$ is the mapping from the target position to the measurements
7. $\mathbf{g} = (g_1, g_2, ..., g_n)^T$ is the localization mapping from the measurements to the target position

Formulation of the bias

In the noisy case, errors in measurements are inevitable. Therefore the localization problem can be formulated as follows:

$$\mathbf{x} + \delta\mathbf{x} = \mathbf{g}(\Theta + \delta\Theta)$$

Next ***a Taylor series*** is used to expand the above equation truncating at second order:

$$\begin{aligned} x_i + \delta x_i &= g_i(\tilde{\theta}_1, \tilde{\theta}_2, ..., \tilde{\theta}_N) \\ &= g_i(\theta_1 + \delta\theta_1, \theta_2 + \delta\theta_2, ..., \theta_N + \delta\theta_N) \\ &\approx g_i(\theta_1, \theta_2, ..., \theta_N) + \sum_{j=1}^{N} \frac{\partial g_i}{\partial \theta_j}\delta\theta_j \\ &\quad + \frac{1}{2!}\sum_{j=1}^{N}\sum_{l=1}^{N} \delta\theta_j \delta\theta_l \frac{\partial^2 g_i}{\partial\theta_j \partial\theta_l} \end{aligned}$$

Formulation of the bias

In the

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follows

The approximate bias expression is immediate:

$$E(\delta x_i) = \frac{1}{2!}\sum_{j=1}^{N} \sigma_j^2 \frac{\partial^2 g_i}{\partial \theta_j^2}$$

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Formulation of the bias

However it is very difficult to compute the localization mapping $\mathbf{g} = (g_1, g_2, ..., g_n)^T$ and its derivatives.

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How to analytically express the bias in an easy way?

Formulation of the bias

However it is very difficult to compute the localization mapping $\mathbf{g} = (g_1, g_2, \ldots, g_n)^T$ and its derivatives. **In contrast** $\mathbf{f} = (f_1, f_2, \ldots, f_N)^T$ **can be easily written down!**

The approximate bias expression is immediate:

$$E(\delta x_i) = \frac{1}{2!} \sum_{j=1}^{N} \sigma_j^2 \frac{\partial^2 g_i}{\partial \theta_j^2}$$

Different Localization Techniques

Range Measurements

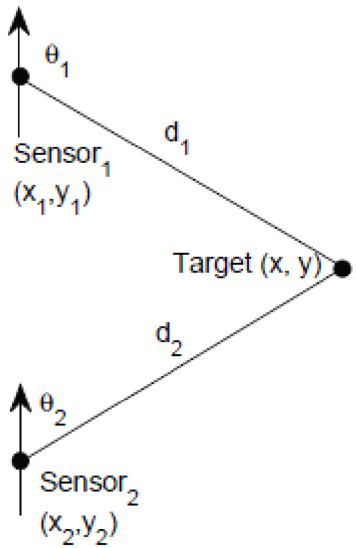
$$d_1 = f_1(x,y) = \sqrt{(x-x_1)^2 + (y-y_1)^2}$$
$$d_2 = f_2(x,y) = \sqrt{(x-x_2)^2 + (y-y_2)^2}$$

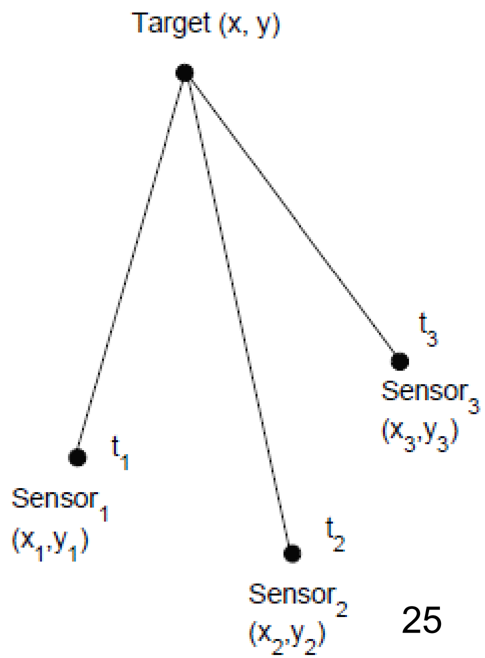
Bearing-Only Measurements

$$\theta_1 = f_1(x,y) = \pi + \text{actan}(\frac{x-x_1}{y-y_1})(\text{mod}2\pi)$$
$$\theta_2 = f_2(x,y) = \text{actan}(\frac{x-x_2}{y-y_2})(\text{mod}2\pi)$$

TDOA Measurements

$$(t_2 - t_1) \times c = f_1(x,y) =$$
$$\sqrt{(x_2-x)^2 + (y_2-y)^2} - \sqrt{(x_1-x)^2 + (y_1-y)^2}$$
$$(t_3 - t_1) \times c = f_2(x,y) =$$
$$\sqrt{(x_3-x)^2 + (y_3-y)^2} - \sqrt{(x_1-x)^2 + (y_1-y)^2}$$





Different Localization Techniques

Range Measurements

$d_1 = f_1(x, y)$

$d_2 = f_2(x, y)$

How to analytically express the bias in an easy way?

Bearing-Only Measurements

$$\theta_1 = f_1(x, y) = \pi + \text{actan}(\frac{x - x_1}{y - y_1})(\text{mod}2\pi)$$

$\theta_2 = f_2(x, y)$

How to analytically express the bias by using ***f* and its derivatives?**

TDOA Me

$$(t_2 - t_1) \times c = f_1(x, y) =$$
$$\sqrt{(x_2 - x)^2 + (y_2 - y)^2} - \sqrt{(x_1 - x)^2 + (y_1 - y)^2}$$
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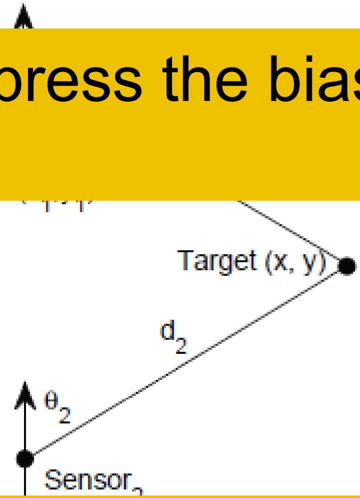

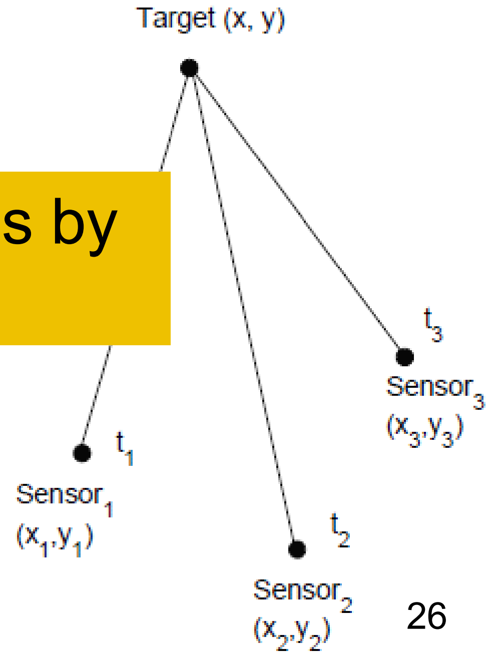

Taylor-Jacobian Bias Correction Method

Jacobian matrix and one of its property are used to calculate the derivatives of g in terms of the derivatives of f.

$$\begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \cdots & \frac{\partial f_1}{\partial x_n} \\ \cdot & \cdots & \cdot \\ \cdot & \cdots & \cdot \\ \cdot & \cdots & \cdot \\ \frac{\partial f_N}{\partial x_1} & \cdots & \frac{\partial f_N}{\partial x_n} \end{bmatrix} \begin{bmatrix} \frac{\partial g_1}{\partial \theta_1} & \cdots & \frac{\partial g_1}{\partial \theta_N} \\ \cdot & \cdots & \cdot \\ \cdot & \cdots & \cdot \\ \cdot & \cdots & \cdot \\ \frac{\partial g_n}{\partial \theta_1} & \cdots & \frac{\partial g_n}{\partial \theta_N} \end{bmatrix} = I_n$$

By solving the above equation set, we can obtain the analytical expression for

$$\frac{\partial g_i}{\partial \theta_j} (i = 1, 2, ..., n; j = 1, 2, ..., N)$$

Taylor-Jacobian Bias Correction Method

Here we take $\frac{\partial g_1}{\partial \theta_1}$ for example. Assume $\frac{\partial g_1}{\partial \theta_1} = g_{\theta_1}^1$, differentiating the equation in respect to $x_1, x_2, \ldots, x_n$ respectively we can obtain the following equation set:

$$\begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \cdots & \frac{\partial f_N}{\partial x_1} \\ \cdot & \cdots & \cdot \\ \cdot & \cdots & \cdot \\ \cdot & \cdots & \cdot \\ \frac{\partial f_1}{\partial x_n} & \cdots & \frac{\partial f_N}{\partial x_n} \end{bmatrix} \begin{bmatrix} \frac{\partial^2 g_1}{\partial {\theta_1}^2} \\ \cdot \\ \cdot \\ \cdot \\ \frac{\partial^2 g_1}{\partial \theta_1 \partial \theta_N} \end{bmatrix} = \begin{bmatrix} \frac{\partial g_{\theta_1}^1}{\partial x_1} \\ \cdot \\ \cdot \\ \cdot \\ \frac{\partial g_{\theta_1}^1}{\partial x_n} \end{bmatrix}$$

Taylor-Jacobian Bias Correction Method

Here we take $\frac{\partial g_1}{\partial \theta_1}$ for example. Assume $\frac{\partial g_1}{\partial \theta_1} = g^1_{\theta_1}$, differentiating the equation in respect to $x_1, x_2, \ldots, x_n$ respectively we can obtain the following equation set:

$$\begin{bmatrix} \frac{\partial f_1}{\partial x_1} & & \frac{\partial f_N}{\partial \cdots} \\ \cdot & & \\ \cdot & & \\ \cdot & & \\ \frac{\partial f_1}{\partial x_n} & \cdots & \frac{\partial f_N}{\partial x_n} \end{bmatrix} \begin{bmatrix} \frac{\partial^2 g_1}{\partial \cdots} \\ \\ \\ \\ \frac{\partial^2 g_1}{\partial \theta_1 \partial \theta_N} \end{bmatrix} \begin{bmatrix} \frac{\partial g^1_{\theta_1}}{\partial x_1} \\ \cdot \\ \cdot \\ \cdot \\ \frac{\partial g^1_{\theta_1}}{\partial x_n} \end{bmatrix}$$

$$E(\delta x_i) = \frac{1}{2!} \sum_{j=1}^{N} \sigma_j^2 \frac{\partial^2 g_i}{\partial \theta_j^2}$$

Can be easily expressed analytically

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Taylor-Jacobian Bias Correction Method

How to analytically express the bias in an easy way?

Solved!

1. Taylor series
2. Jacobian matrix and its property

So we call the proposed method as ***Taylor-Jacobian*** bias correction method.

Overdetermined Problem

Jacobian matrix and one of its property

$$\begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \cdots & \frac{\partial f_1}{\partial x_n} \\ \cdot & \cdots & \cdot \\ \cdot & \cdots & \cdot \\ \cdot & \cdots & \cdot \\ \frac{\partial f_N}{\partial x_1} & \cdots & \frac{\partial f_N}{\partial x_n} \end{bmatrix} \begin{bmatrix} \frac{\partial g_1}{\partial \theta_1} & \cdots & \frac{\partial g_1}{\partial \theta_N} \\ \cdot & \cdots & \cdot \\ \cdot & \cdots & \cdot \\ \cdot & \cdots & \cdot \\ \frac{\partial g_n}{\partial \theta_1} & \cdots & \frac{\partial g_n}{\partial \theta_N} \end{bmatrix} = I_n$$

Important assumption: ***N=n***

Overdetermined Problem

Jacobian matrix and one of its property

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Important assumption: ***N>n***

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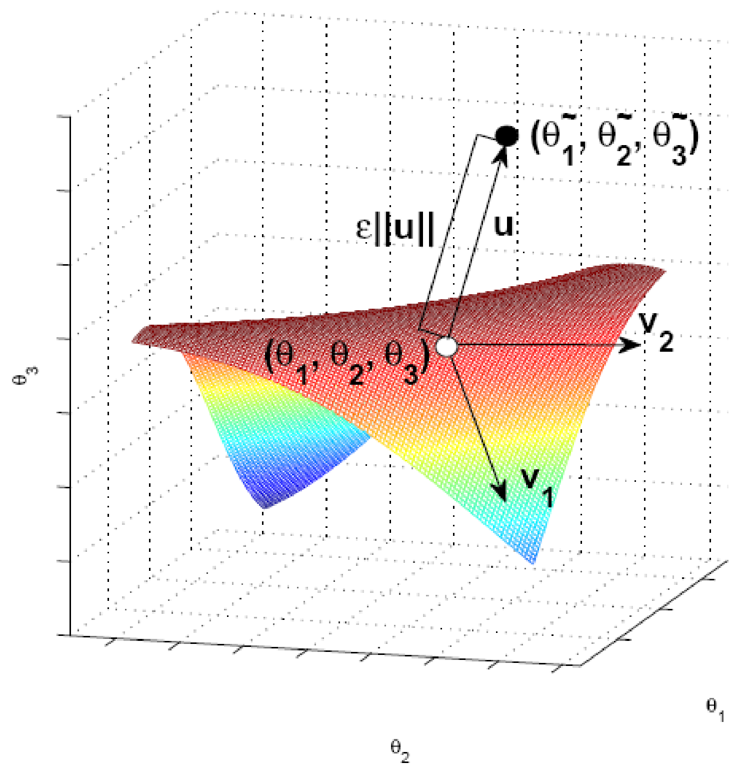
Overdetermined Problem (N=n+1)

Least squares method:

$$F_{\text{cost-function}}(\mathbf{x}, \tilde{\Theta}) = \sum_{i=1}^{N} (f_i - \tilde{\theta}_i)^2 = \sum_{i=1}^{N} \delta\theta_i^2$$



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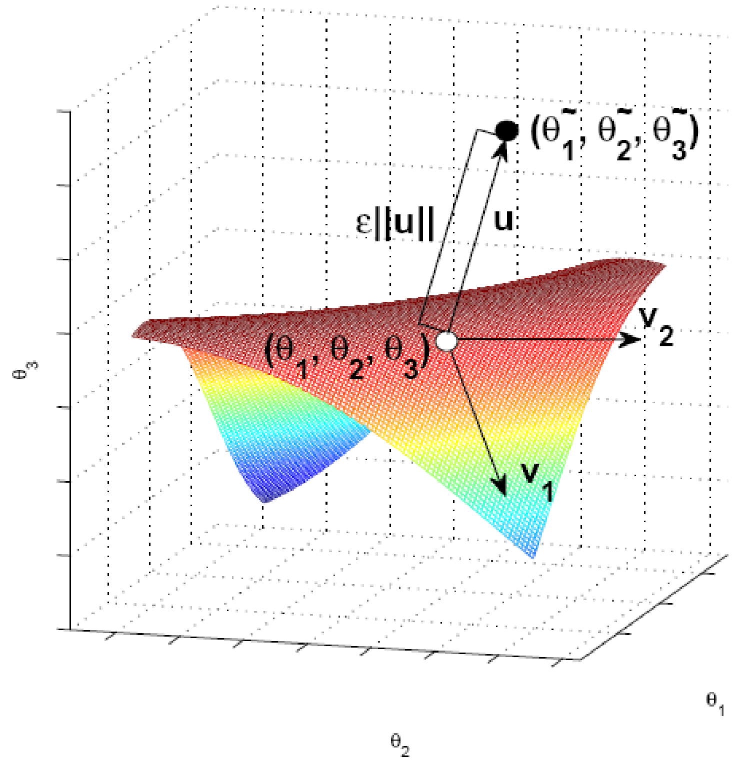
Minimize the distance:

$$D_{\min} = \sqrt{\sum_{i=1}^{N} \delta\theta_i^2} = \varepsilon||\mathbf{u}||$$



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Minimize the distance:

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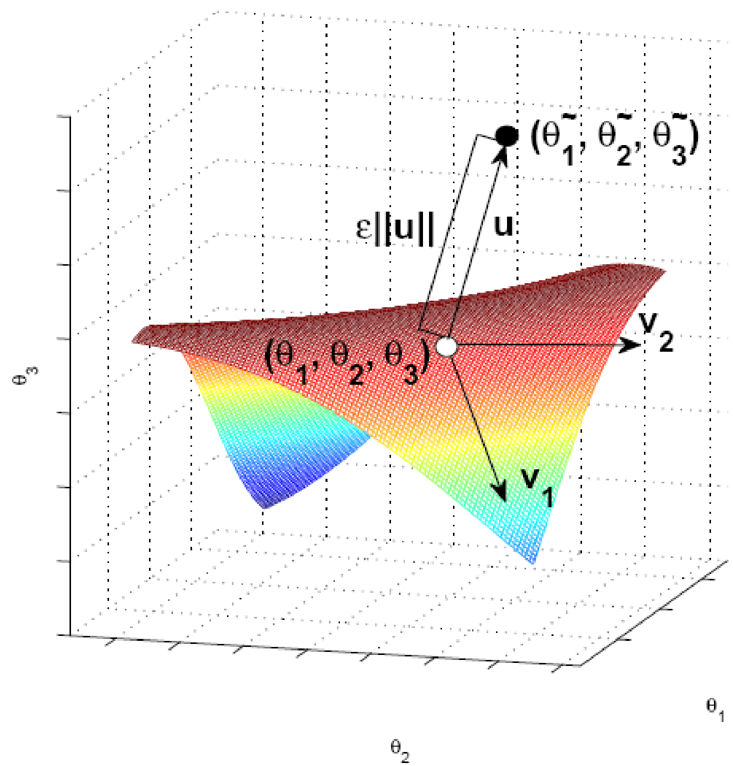
For the white point:

$$\mathbf{v}_i = [\frac{\partial f_1}{\partial x_i}, \frac{\partial f_2}{\partial x_i}, ..., \frac{\partial f_N}{\partial x_i}]^T \quad i = 1, 2, ..., n$$



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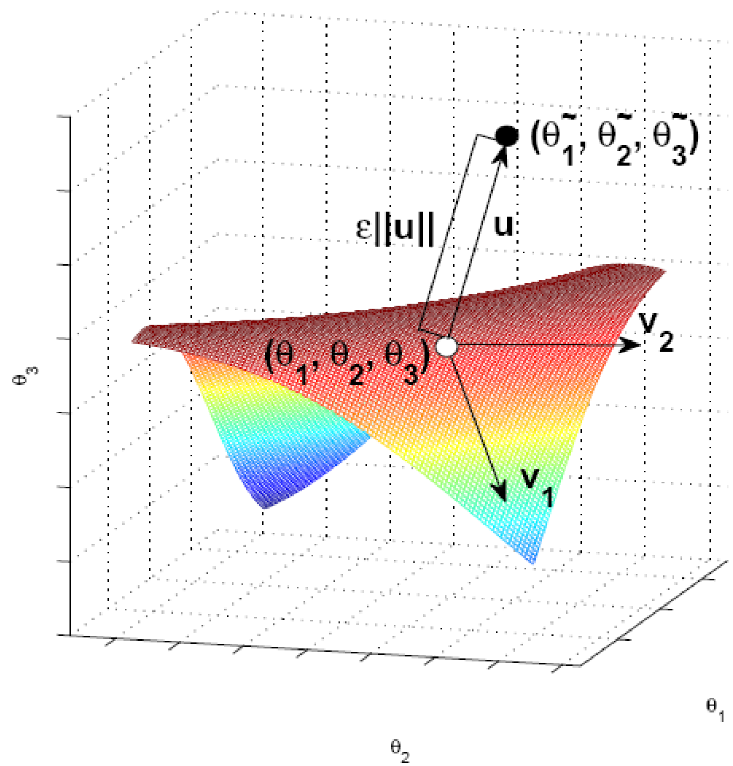
The normal vector:

$$\mathbf{u} = [u_1, u_2, ..., u_N]^T = \mathbf{v}_1 \times \mathbf{v}_2 ... \times \mathbf{v}_n$$



Overdetermined Problem (N=n+1)

Least squares method:

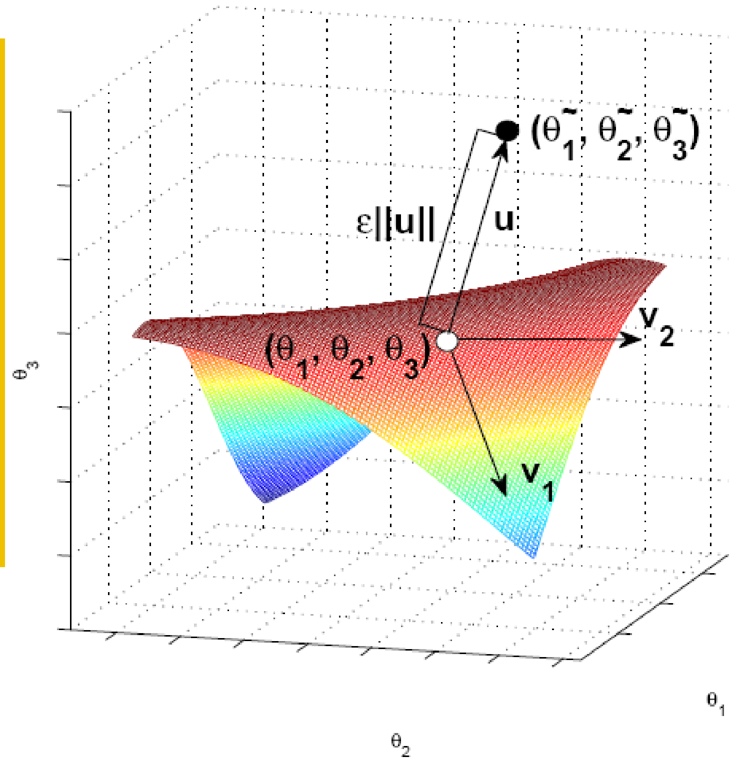
Finally we can obtain a new mapping:

$$\tilde{\Theta} = \mathbf{F}(\tilde{\mathbf{x}}, \varepsilon) = \mathbf{f}(\tilde{\mathbf{x}}) + \varepsilon \mathbf{u}$$

$$\mathbf{v}_i = [\frac{\partial f_1}{\partial x_i}, \frac{\partial f_2}{\partial x_i}, ..., \frac{\partial f_N}{\partial x_i}]^T \quad i = 1, 2, ..., n$$

The normal vector:

$$\mathbf{u} = [u_1, u_2, ..., u_N]^T = \mathbf{v}_1 \times \mathbf{v}_2 ... \times \mathbf{v}_n$$



Overdetermined Problem (N>n+1)

With N> n+1, the situation is similar to N=n+1 case except that the extra variable is no longer a scalar. Instead, it is a vector which can be defined as follows:

$$\varepsilon = [e_1, e_2, ..., e_{N-n}]^T$$

Where $e_i \ (i = 1, 2, ..., N - n)$ denotes a coefficient to minimize the moved distance in each dimension of the normal.

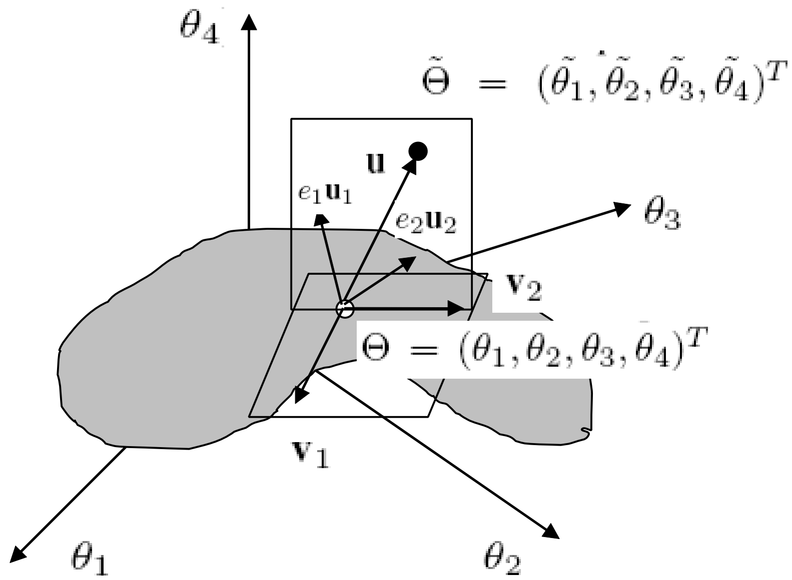
Overdetermined Problem (N>n+1)

Assume N=4 and n=2.

At the white point we can have:

$$\mathbf{v}_1 = [\frac{\partial f_1}{\partial x_1}, \frac{\partial f_2}{\partial x_1}, \frac{\partial f_3}{\partial x_1}, \frac{\partial f_4}{\partial x_1}]^T$$

$$\mathbf{v}_2 = [\frac{\partial f_1}{\partial x_2}, \frac{\partial f_2}{\partial x_2}, \frac{\partial f_3}{\partial x_2}, \frac{\partial f_4}{\partial x_2}]^T$$



These two tangent vectors define a tangent plane $\mathbf{P}_{tangent}$

Contributions and key mathematic tools of our work

Contributions:

1. Express the bias in an easy way by using the function ***f*** (mapping from the target position to the measurements) and its derivatives

2. Adopt a method based on least-squares idea to solve the overdetermined problem

Mathematic tools:

1. Taylor series

2. Jacobian Matrix

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Outline

- Motivation
- Bias in Localization Problem
- Taylor-Jacobian Bias Correction Method
- Performance Evaluation and Simulation
- Conclusion

Simulation

Simulation Assumption

• All simulations are done in two-dimensinol space

• The three sensors are fixed at (0, 8), (0, -8) and (8,0)

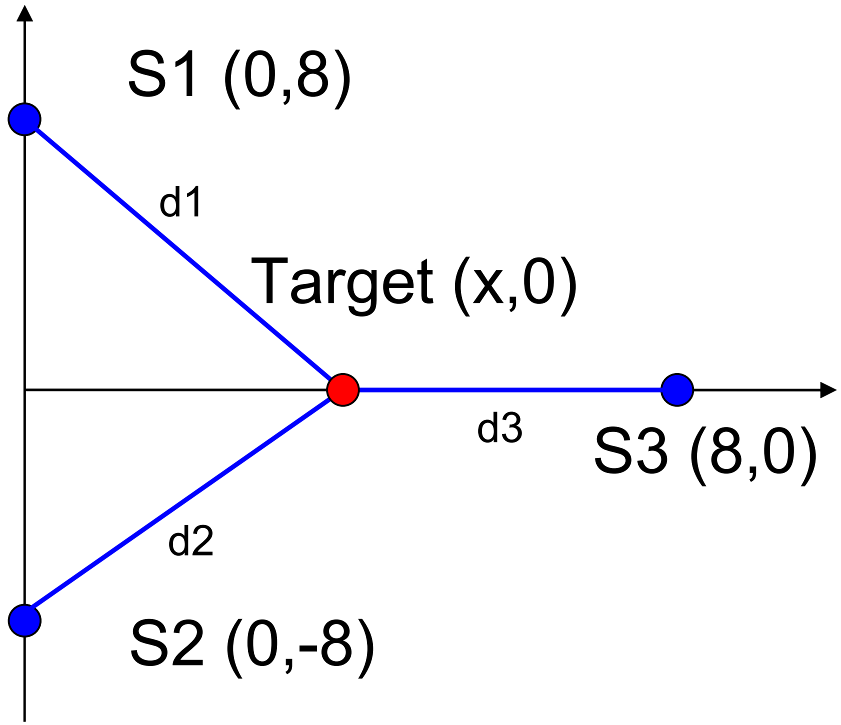
• The measurement noise for three sensors are produced by i. i. d. Gaussian with zero mean and variance $\sigma^2 = 1$.

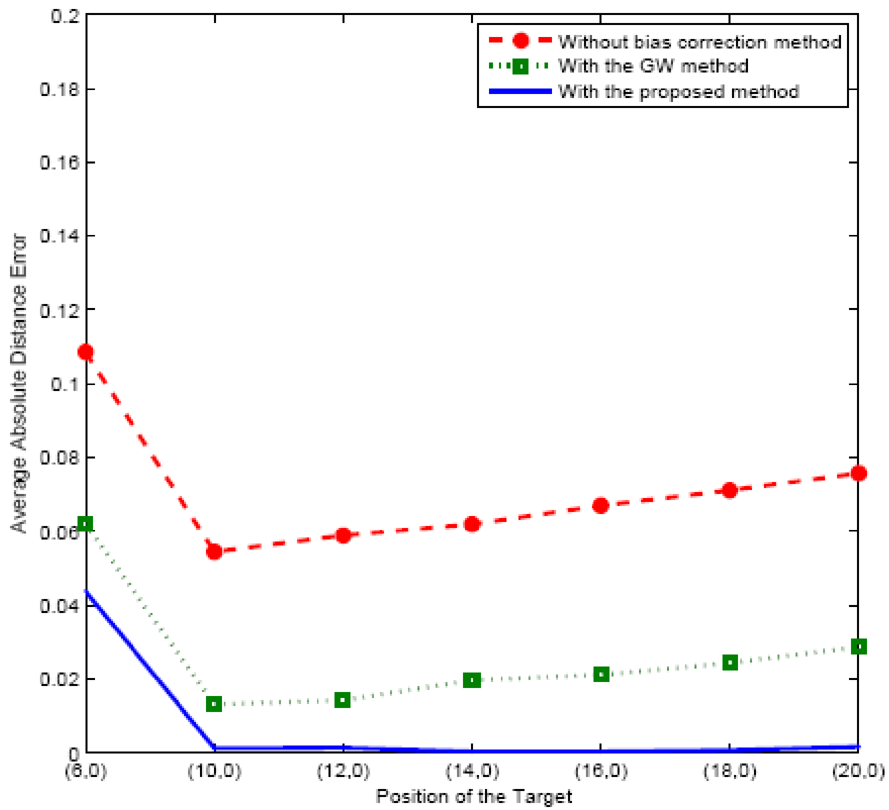
• All the simulation results are obtained from 5000 Monte Carlo experiments.

• We compare our method with an well-cited bias-correction method GW method [1]

[1] M. Gavish and A. J. Weiss. Performance analysis of bearing-only target location algorithms. IEEE Transaction on Aerospace and Electronic Systems, 28(3): 817-827, 1992.

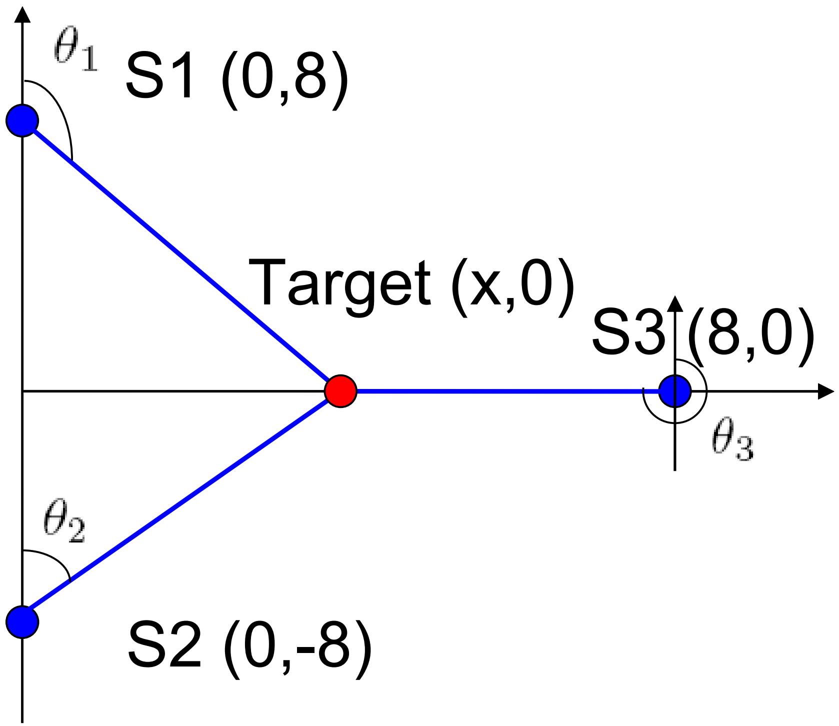
Simulation Results - Range Measurement

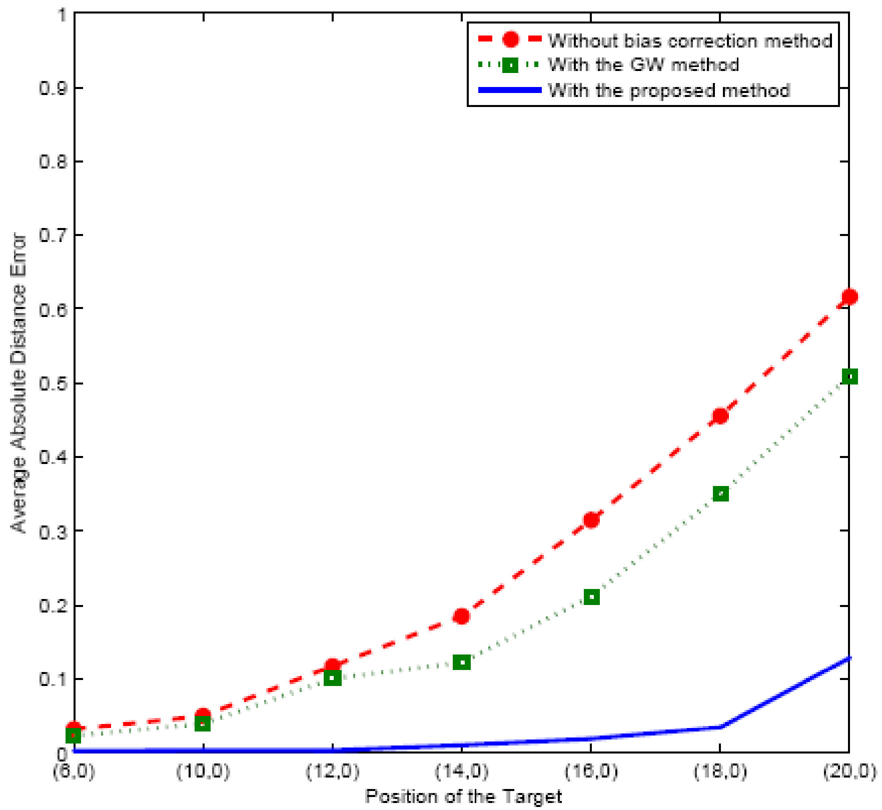




- Three sensors and a single target
- Range measurements only
- Measurement errors are $\mathcal{N}(0,1)$
- The y value of the target is fixed at 0; x value is adjusted from 6 to 20

Simulation Results – Bearing-Only Measurement

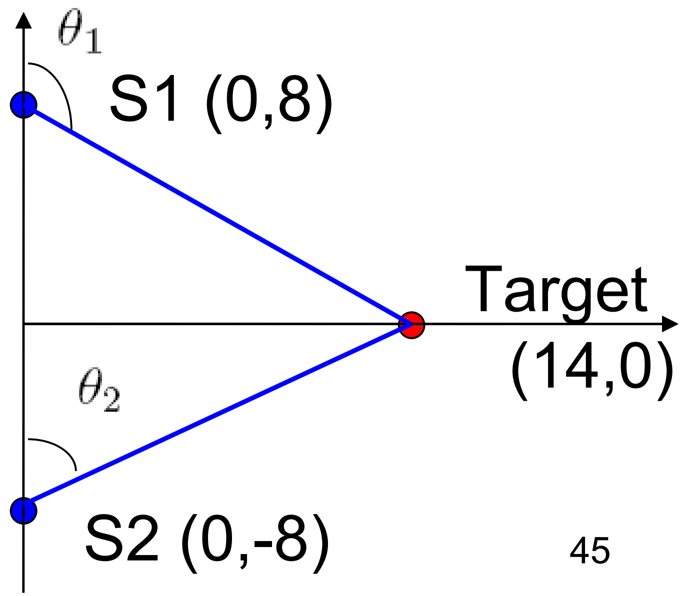




- Three sensors and a single target
- Bearing-only measurements
- Measurement errors are $\mathcal{N}(0,1)$
- The y value of the target is fixed at 0; x value is adjusted from 6 to 20

Simulation Results - Different Level of Noise

- Truncation of Taylor series is not necessarily justified when the noise is large
- Noise level is adjusted over a large range via changing the standard deviation of measurement errors, from 0.5 to 3.5 in steps of 0.5
- Bearing-only measurements are used



Simulation Results - Different Level of Noise

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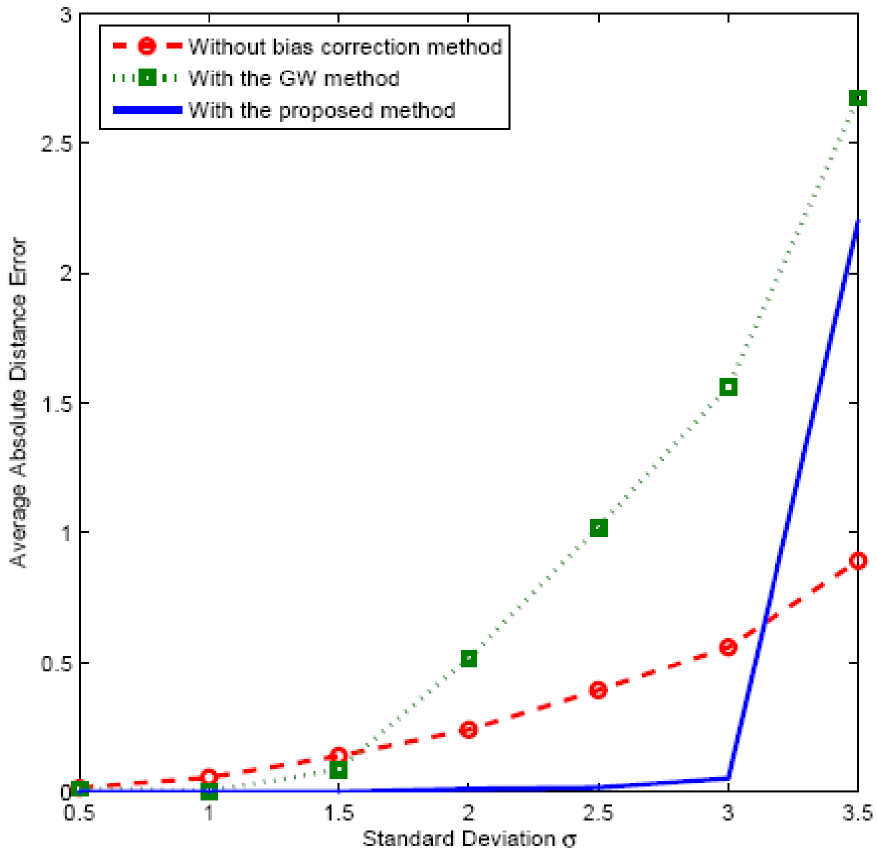
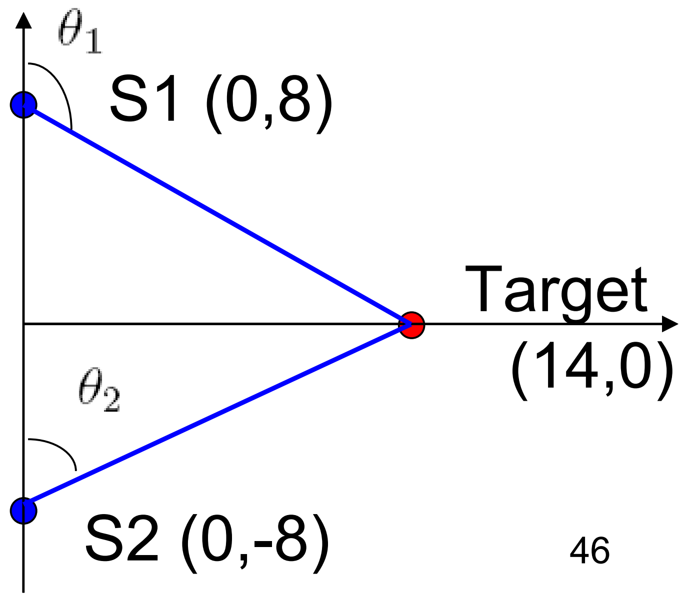
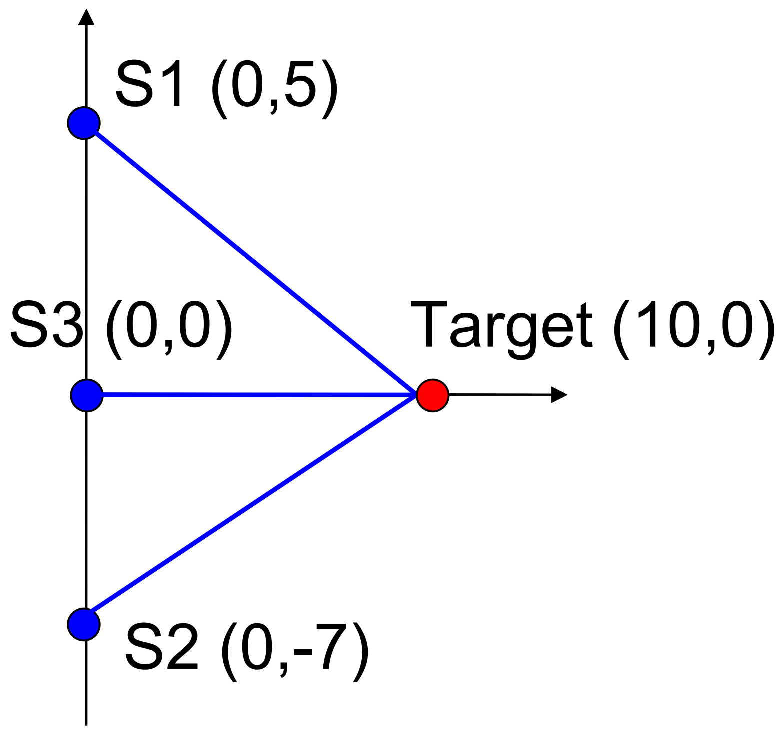




Trial Data – Scan-based Measurement



- Three physical sensors and a single target, which is a radar with a mechanically rotating antenna.
- Two usable sensor measurements are obtained.
- Noise in measurements is N(0,0.02)

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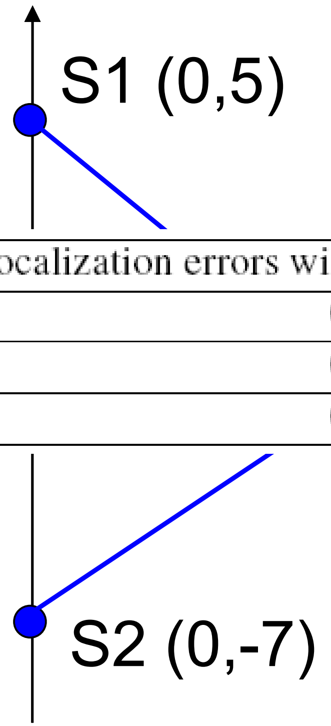
Trial Data – Scan-based Measurement



- Three physical sensors and a single target, which is a radar

Localization errors without bias-correction method	Localization errors with bias-correction method
0.6610	0.0785
0.3435	0.0462
0.3454	0.0465

measurements are obtained.

- Noise in measurements is N(0,0.02)

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Performance of the Taylor-Jacobian Method

1. The Taylor-Jacobian method is generic
    - Range Measurement
    - Bearing-only Measurement
    - Scan-based Measurement
- The performance of the Taylor-Jacobian method is better than the GW method
- The Taylor-Jacobian method can be more robust to the level of noise than the GW method

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Conclusion

- Bias arises due to simultaneous presence of noise and nonlinear transformations.
- In localization, the map need for computing the bias may not be analytically available; its inverse is available so the bias computation needs to be varied
- A generic Taylor-Jacobian bias correction method is proposed
- The simulation results demonstrate the performance of the proposed method

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Thank you!

Publications:

[1] Y. Ji, C. Yu and B. D. O. Anderson. Bias correction in localization algorithms. IEEE Global Communication Conference, pp. 1-7, 2009.

[2] Y. Ji, C. Yu and B. D. O. Anderson. Geometric dilution of localization and bias-correction methods. International Conference on Control & Automation, pp. 578-583, 2010.

[3] Y. Ji, C. Yu and B. D. O. Anderson. Localization bias correction in n-dimensional space. IEEE International Conference on Acoustics Speech and Signal Processing, pp. 2854-2857, 2010.

[4] Y. Ji, C. Yu and B. D. O. Anderson. Bias-correction method in bearing-only passive localization. European Signal Processing Conference, Published, 2010.

[5] Y. Ji, C. Yu and B. D. O. Anderson. Localization bias correction in n-dimensional space. Submitted to IEEE Transaction on Aerospace and Electronic Systems.

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