CS649
Sensor Networks
Lecture IP-10: Sensor Calibration

I-Jeng Wang
http://hinrg.cs.jhu.edu/wsn06/

Sensor Calibration

- Traditional Sensor Calibration: The process of forcing a sensor to conform to a given input/output mapping
  - Perform for each sensor individually in a controlled environment
  - Rely on a set of specific stimuli with known results (inputs and their expected outputs)
- Calibration in Sensor Network
  - A large number of sensors typically with no calibration interface
  - Access to individual sensors in the field can be limited
  - Require calibration in a complex dynamic environment with many unobservables
  - Reference stimuli might not be readily available
  - Sensor states can drift (aging, decay, damage, etc.)
  - Different applications will require different calibration

Type of Calibration in Sensor Networks

- Off-line versus On-line
  - Performed before or during sensor network operations
  - How the “correct values” are generated
- Supervised versus Unsupervised (autocalibration)
  - Rely on any given ground truth (input and expected output pair) or not
- Passive versus Active
  - Whether the stimuli are controllable
- Absolute versus Relative

Macro-calibration in Sensor/Actuator Networks

K. Whitehouse and D. Culler

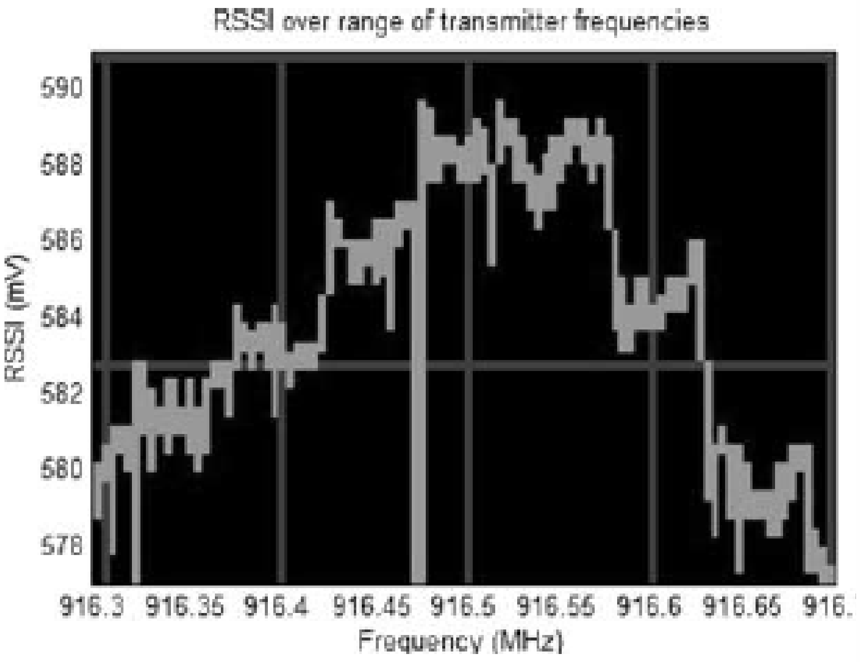
Mobile Networks and Applications Journal (*MONET*), *Special Issue on Wireless Sensor Networks*, June, 2003.

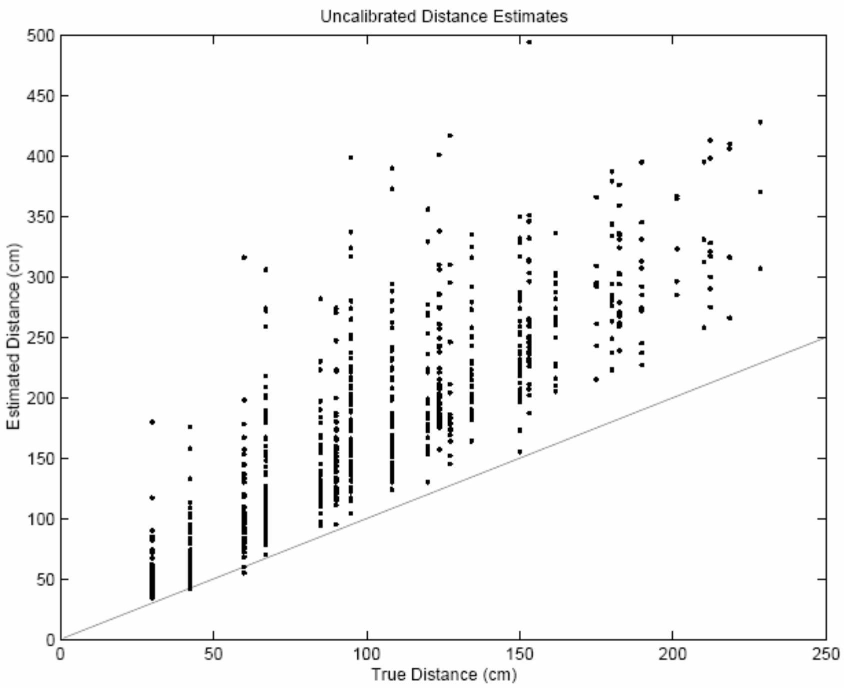
Summary

- Formulate calibration as a parameter estimation problem
- Focus on off-line calibration of ranging for self-localization with given ground truth
- Joint calibration to optimize network-wide performance
- Extension to autocalibration

Need for Calibration

- Calamari ad-hoc localization system:
  - TDOA ranging with RF and Acoustic





Traditional Calibration

- Observe the device in a controlled environment and map its output r to the desired out put r^* by a *calibration function*

$$r^* = f(r, \beta).$$

- To calibrate for ranging, we can estimate β_i given the true distances

$$d_1^* = \beta_1 + \beta_2 d_1,$$
$$d_2^* = \beta_1 + \beta_2 d_2,$$
$$d_3^* = \beta_1 + \beta_2 d_3.$$

- *Separation Problem*: result of each calibration ties to the specific transmitter/receiver pair

Approaches to Address the Separation Problem (Micro-Calibration)

- *Iterative Calibration*: Declares one transmitter as the reference transmitter; calibrate all receivers; pick one receive as a reference; calibrate all transmitter

$$d_i^* = f(d_i, \beta_i)$$

$$d_j^* = f(d_j, \beta_j, \hat{\beta}_r)$$

  - Issue: Receiver's calibration parameters depend on the transmitting frequency (hence the transmitter)
- *Mean Calibration*: Calibrate each receiver for all transmitters, obtain d^* for all transmitter and solve for β_i

$$d_{i,j}^* = f(d_{i,j}, \beta_i)$$

  - Minimize expected error

Macro-calibration: Joint Calibration in Calamari

- Basic Steps:
  - Parameterize each individual device and model the system response as a whole using these parameter
  - Collect data from the system as a whole
  - Choose the parameters to optimize the system-level performance
- Parameterization

$$\begin{aligned} d^* = {} & \overbrace{B_{\mathrm{T}} + B_{\mathrm{R}}}^{\text{Bias}} + \overbrace{G_{\mathrm{T}} d + G_{\mathrm{R}} d}^{\text{Gain}} \\ & + \underbrace{|F_{\mathrm{T}} - F_{\mathrm{R}}| d}_{\text{Frequency}} + \underbrace{f_{\mathrm{O}}(O_{\mathrm{T}}, O_{\mathrm{R}}) d}_{\text{Orientation}}, \end{aligned}$$

Least Square for Joint Calibration

$$r^* = B_{\mathrm{T}} + B_{\mathrm{R}} + G_{\mathrm{T}} r + G_{\mathrm{R}} r.$$

$$d^*_{i,j} = f(d_{i,j}, \beta_i, \beta_j)$$ for R_i and T_j

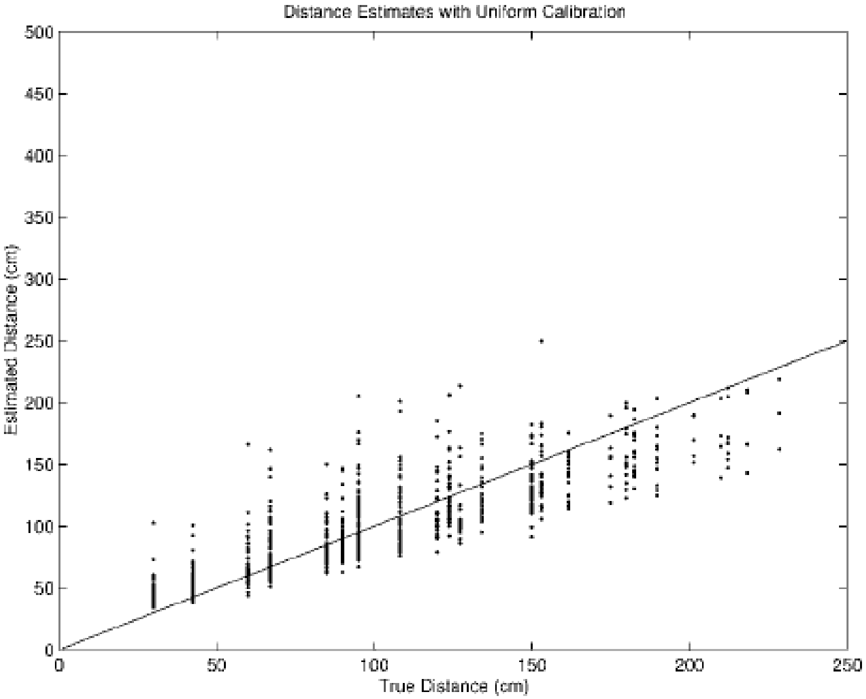
$$Ax = b.$$

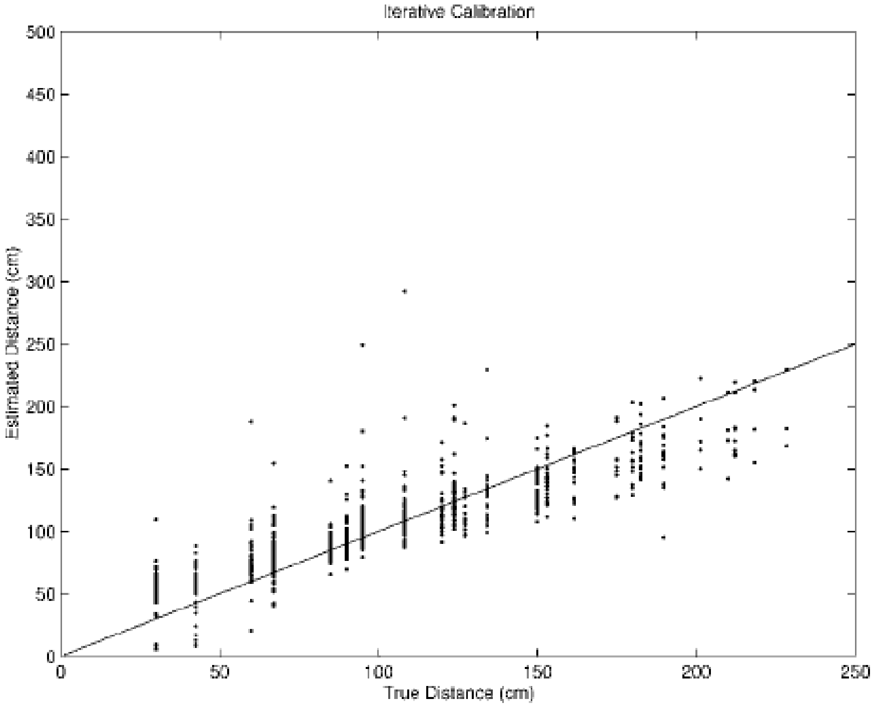
$$b = \begin{pmatrix} d^*_{1,2} \\ d^*_{1,3} \\ \vdots \end{pmatrix}$$

$$x = \begin{pmatrix} B_{\mathrm{T}_1} \\ \vdots \\ B_{\mathrm{T}_n} \\ B_{\mathrm{R}_1} \\ \vdots \\ B_{\mathrm{R}_n} \\ G_{\mathrm{T}_1} \\ \vdots \\ G_{\mathrm{T}_n} \\ G_{\mathrm{R}_1} \\ \vdots \\ G_{\mathrm{R}_n} \end{pmatrix}.$$

$$A = \begin{pmatrix} 1 & 0 & \ldots & 0 & 1 & 0 & \ldots & d_{1,2} & 0 & \ldots & 0 & d_{1,2} & 0 & \ldots \\ 1 & 0 & \ldots & 0 & 0 & 1 & \ldots & d_{1,3} & 0 & \ldots & 0 & 0 & d_{1,3} & \ldots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \end{pmatrix}$$

Experiment Results

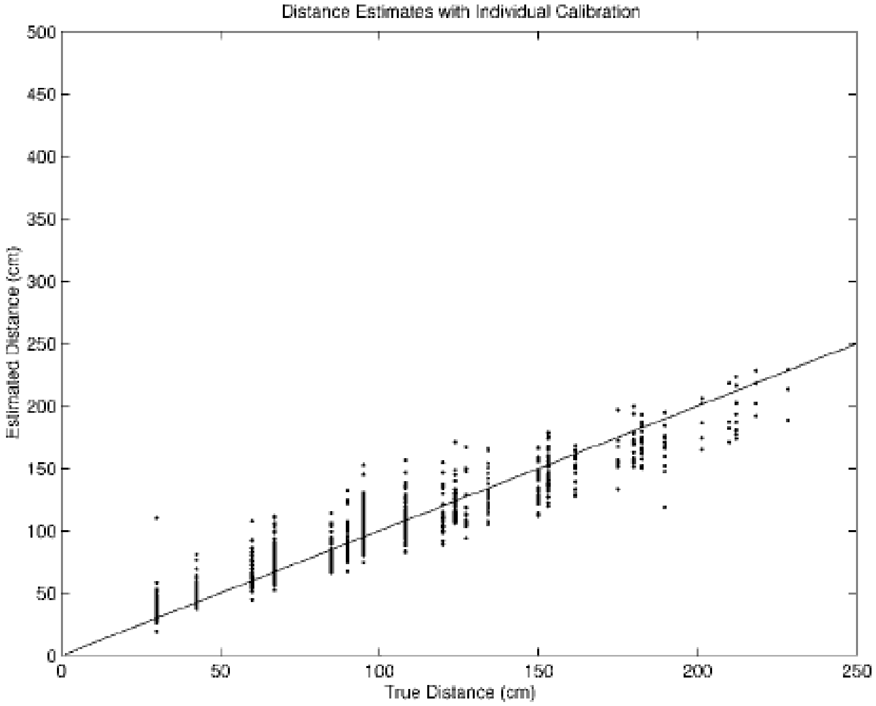


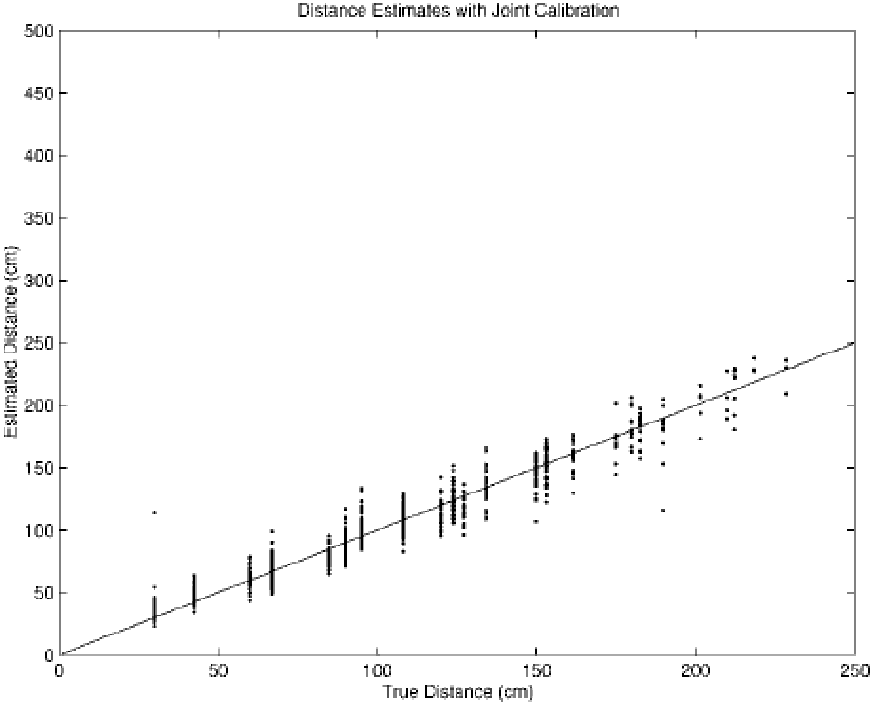


Uniform Calibration: average error 21%

Iterative Calibration: average error 19.7%

Experiment Results





Mean Calibration: average error 16%

Joint Calibration: average error 10.1%

Extension to Autocalibration

- No true distance is given
- Formulate calibration as a constrained optimization problem to maximize the consistency of the responses between symmetric pairs using *a priori* information

$$d^*_{ij} = d^*_{ji}, \quad d^*_{ij} = B_{\mathrm{T}_i} + B_{\mathrm{R}_j} + G_{\mathrm{T}_i} d_{ij} + G_{\mathrm{R}_j} d_{ij}$$

Minimize

$$\sum_{i<j} (d^*_{ij} - d^*_{ji})^2 + \sum_i (G_{\mathrm{T}_i} - 1)^2 + \sum_i (G_{\mathrm{R}_i} - 1)^2$$

subject to $d^*_{ij} + d^*_{jk} - d^*_{ik} \geq 0 \quad \forall\, triangle_{i,j,k}$.

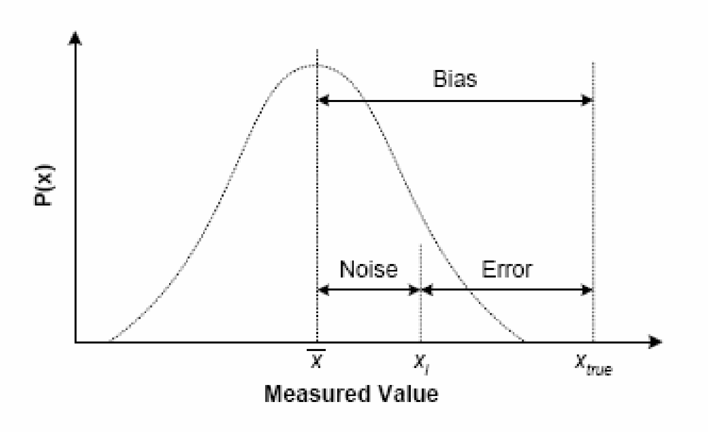
A Collaborative Approach to In-Place Sensor Calibration

V. Bychkovskiy, S. Megerian, D. Estrin, and M. Potkonjak

IPSN 2003.

Summary

- Unsupervised calibration to account for systematic error without known stimuli
- Exploit redundancies in sensor measurements under dense deployments to derive pair-wise calibration functions (relative calibration)
- A two-phase post-deployment technique
  - Phase I: Derive pair-wise calibration functions for co-located sensor pairs
  - Phase II: Maximize consistency of pair-wise functions among groups of nodes

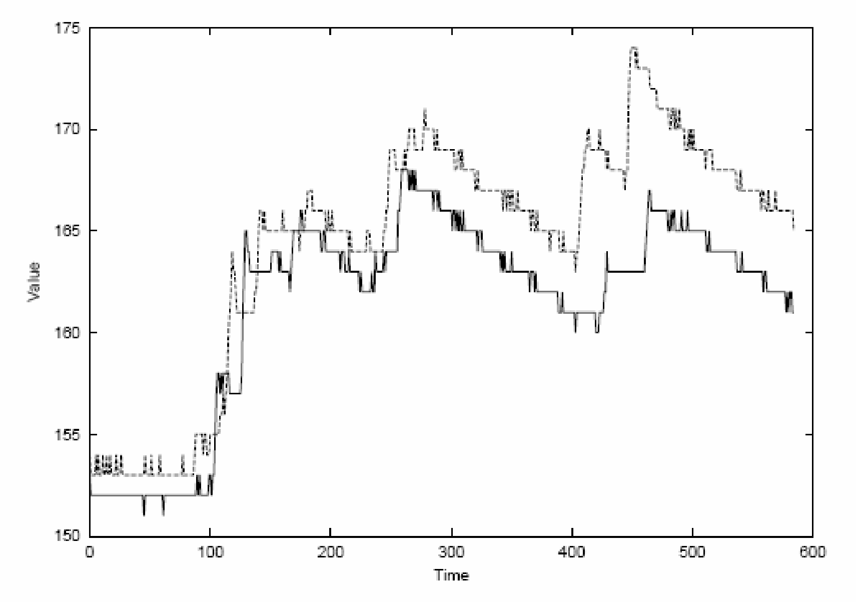


Key Assumptions

- Phenomenon
  - Known and limited spatial frequency
  - High temporal frequency
- Sensors:
  - Dense deployment
  - No sensor state drifting during calibration
  - No angle-dependent gains in sensor measurements
  - No significant delay in sensor response

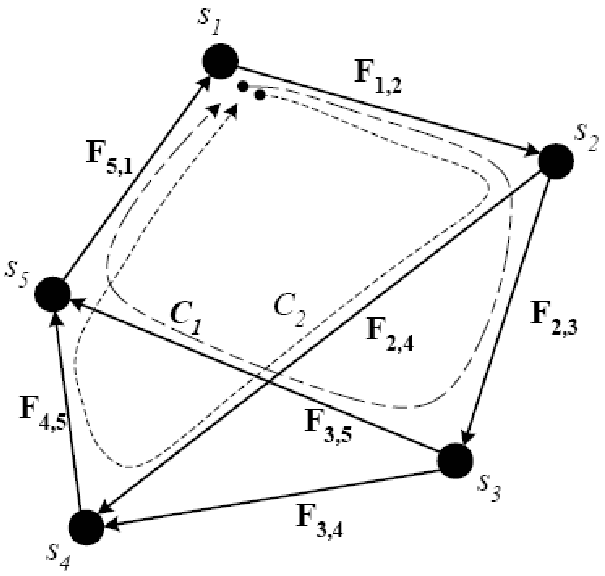
Phase 1: Pair-Wise Calibration Functions

- For pair of co-located sensors
  - Collect time-series data in a synchronized manner
  - Identify and weight potential data points based on correlation analysis
  - Filter our irrelevant data points (with lower correlation)
  - Fit a calibration function to the filtered data set



$F_{i,j}(x)$: mapping the output of sensor i to sensor j

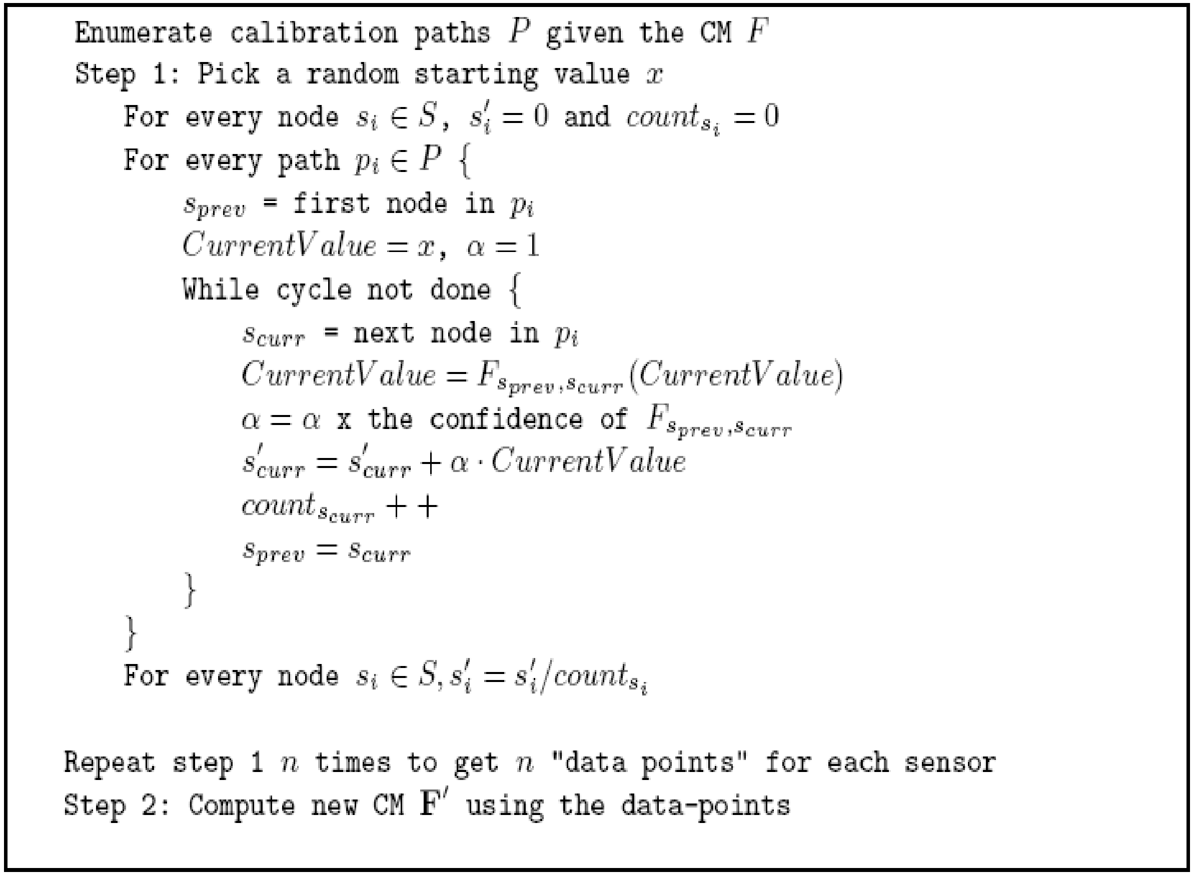
Phase 2: Localized Consistency Maximization



$$\mathbf{C_1} : \mathbf{s}_1' = F_{5,1}(F_{3,5}(F_{2,3}(F_{1,2}(s_1))))$$

$$\mathbf{C_2} : \mathbf{s}_1'' = F_{5,1}(F_{4,5}(F_{2,4}(F_{1,2}(s_1))))$$

$$s_1 \neq s_1' \neq s_1''$$



```
Enumerate calibration paths $P$ given the CM $F$
Step 1: Pick a random starting value $x$
    For every node $s_i \in S$, $s_i' = 0$ and $count_{s_i} = 0$
    For every path $p_i \in P$ {
        $s_{prev}$ = first node in $p_i$
        $CurrentValue = x$, $\alpha = 1$
        While cycle not done {
            $s_{curr}$ = next node in $p_i$
            $CurrentValue = F_{s_{prev},s_{curr}}(CurrentValue)$
            $\alpha = \alpha$ x the confidence of $F_{s_{prev},s_{curr}}$
            $s_{curr}' = s_{curr}' + \alpha \cdot CurrentValue$
            $count_{s_{curr}}++$
            $s_{prev} = s_{curr}$
        }
    }
    For every node $s_i \in S, s_i' = s_i'/count_{s_i}$

Repeat step 1 $n$ times to get $n$ "data points" for each sensor
Step 2: Compute new CM $\mathbf{F}'$ using the data-points
```

Other Related Work on Calibration in Sensor Networks

- J. Feng, G. Qu, and M. Potkonjak, “Differential On-line Sensor Calibration,” *IEEE* Sensors'2004, 2004.
  - Using actuators (signal sources) to enable on-line calibration
  - Formulate the calibration problem as a maximal likelihood based optimization problem
- Mark A. Paskin, and Carlos E. Guestrin “Robust Probabilistic Inference in Distributed Systems,” *UAI-04*, 2004.
  - Construct a graphical model that characterize the dependencies among sensor readings, bias, and unknown truth

$$\underbrace{\left[\frac{1}{Z}\prod_{(i,j)\in\mathcal{E}}\psi_{ij}(T_i,T_j)\right]}_{\text{temperature prior}}\prod_{i\in\mathcal{N}}\underbrace{\Pr\{B_i\}}_{\text{bias prior}}\underbrace{\Pr\{M_i\,|\,B_i,T_i\}}_{\text{measurement model}},$$

  - Using junction tree algorithm to obtain the posterior distribution of the truth and bias given measurements

$$\Pr\left\{T_i, B_i \,\middle|\, \overline{m}_1, \ldots, \overline{m}_N\right\}$$

A More General View: Dynamic Self-Calibration in Sensor Networks

- Autonomously adapt local signal and information processing algorithms to address impacts of unpredictable operating conditions (e.g. background noise characteristics) and sensor states (e.g. sensor orientation) *after* deployment
- A spectrum of calibration problems
  - Self-localization, synchronization
  - Calibration of sensor measurements
  - Adaptation of local information processing algorithms

Many Key Issues Remain Unsolved!

- Generalization of the Calibration Functions: Why do we calibrate? So that the sensor network performs well in the future for situations that it might not have encountered!
  - Parameterization (Model Selection): Model-based versus Non-parametric
  - Active learning problem: what are the right stimulus?
- Cost associated with on-line calibration
- Tools from Statistical Learning Theory can be quite relevant
  - VC dimension and learnability
  - Large margin regression
- Dynamic environment, reactive calibration, calibration and fault detection?