

Objectives

- Review the classical LS solution of the TDOA-based source localization problem
- Employ data-selection to this solution
- Show the performance of the new approach
- Point out scenarios for this new solution

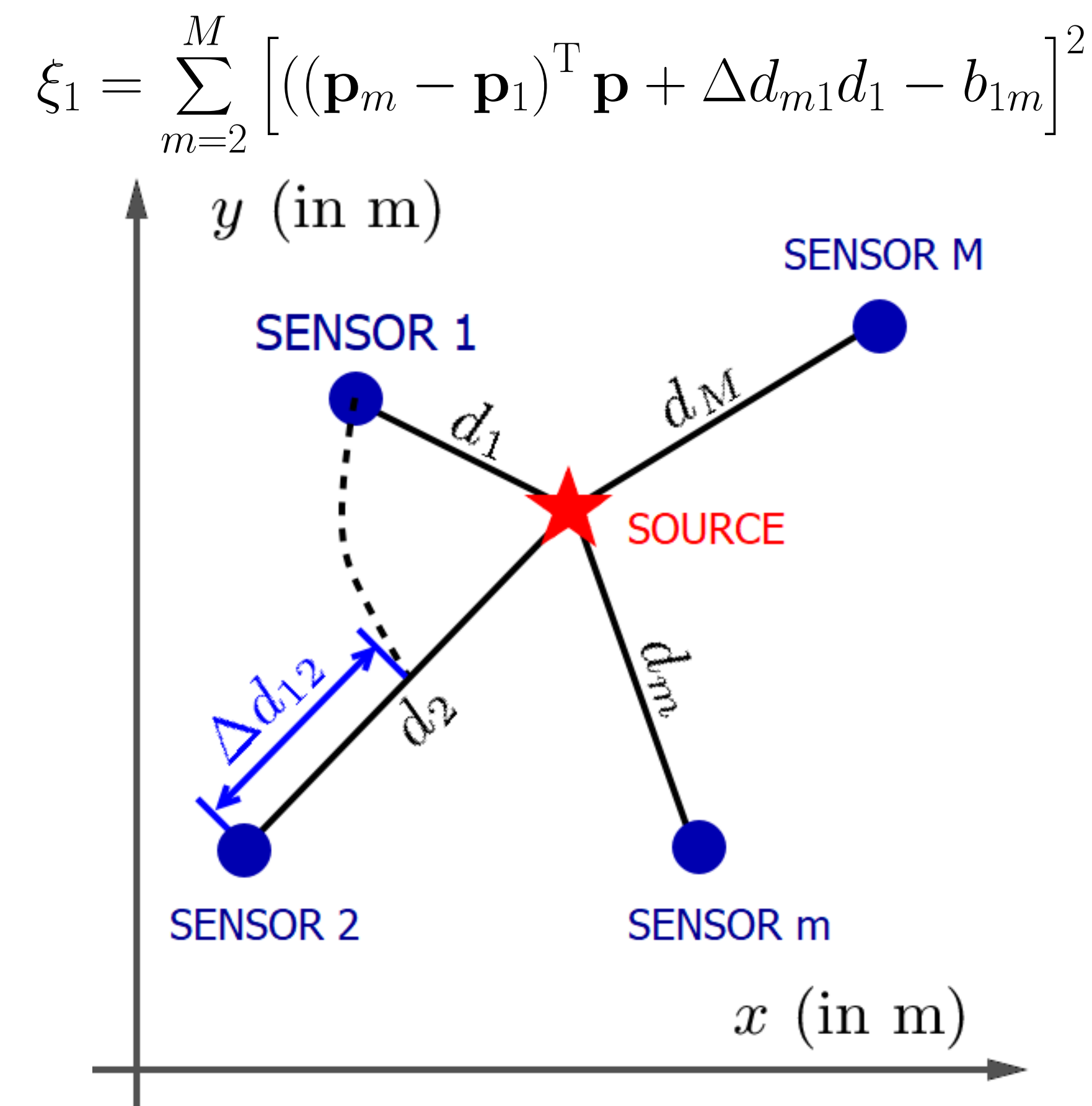
Introduction

- The source localization problem has applications in many fields
- Usual strategies: received signal strength (RSS), direction of arrival (DOA), time of arrival (TOA), and time difference of arrival (TDOA)
- The TDOA strategy measures the difference of transmission time of a single signal between the receiver nodes
- It has a closed form, is more robust to reflections and easier to implement (lower computational burden and requiring no sensor arrays)
- The signal from the sensors must be synchronized

The Classical Approach

- In a 2D scenario, M sensors with known positions given by \mathbf{p}_m , $1 \leq m \leq M \Rightarrow N = \frac{M(M-1)}{2}$ TDOAs
- We define the range-difference from the unknown source and sensors i and j : $\Delta d_{ij} = d_i - d_j = \frac{v\tau_{ij}}{f_s}$, $i > j$
- The TDOA τ_{ij} (in number of samples) is obtained from the peak of the cross-correlation of the signals acquired by the sensors
- For the m -th sensor, d_m is the distance from the source (unknown position \mathbf{p}) to the m -th sensor
- Therefore, we can write $\|\mathbf{p} - \mathbf{p}_1\|^2 = d_1^2$ and $\|\mathbf{p} - \mathbf{p}_m\|^2 = (d_1 + \Delta d_{m1})^2 \dots$
- \dots which leads to $(\mathbf{p}_m - \mathbf{p}_1)^T \mathbf{p} + \Delta d_{m1}d_1 = b_{1m}$, where $b_{1m} = \frac{\|\mathbf{p}_m\|^2 - \|\mathbf{p}_1\|^2 - \Delta d_{m1}^2}{2}$, $2 \leq m \leq M$

The LS Cost Function



The closed-form solution

- ξ_1 can be expressed $\|\mathbf{e}_1\|^2$ where

$$\mathbf{e}_1 = \begin{bmatrix} (\mathbf{p}_2 - \mathbf{p}_1)^T & \Delta d_{21} \\ (\mathbf{p}_3 - \mathbf{p}_1)^T & \Delta d_{31} \\ \vdots & \vdots \\ (\mathbf{p}_M - \mathbf{p}_1)^T & \Delta d_{M1} \end{bmatrix} \begin{bmatrix} \mathbf{p} \\ d_1 \end{bmatrix} - \begin{bmatrix} b_{12} \\ b_{13} \\ \vdots \\ b_{1M} \end{bmatrix}$$

- Note (in a 2D scenario) that \mathbf{A}_1 is an $(M-1) \times 3$ matrix \rightsquigarrow if we have at least four sensors, an unconstrained solution is obtained after $\nabla_{\mathbf{x}_1} \xi_1 = \mathbf{0}$
- The estimated position of the source is given by $\hat{\mathbf{p}} = [\mathbf{I} \ \mathbf{0}] \hat{\mathbf{x}}_1 = [\mathbf{I} \ \mathbf{0}] (\mathbf{A}_1^T \mathbf{A}_1)^{-1} \mathbf{A}_1^T \mathbf{b}_1$

Key Concept

We next extend the number of pairs from $(M-1)$ to $\frac{M(M-1)}{2}$ (as in [Khalaf-Allah, 2014]) and, assuming a number of incorrect TDOAs estimates, propose a criterion to select those leading to better results!

Using more TDOAs

- The previous solution uses only $M-1$ from a total of $N = \frac{M(M-1)}{2}$ TDOA measurements
- Assuming similar errors, we expect that using more measurements leads to more accurate results
- Using $\|\mathbf{p} - \mathbf{p}_m\|^2 = (d_2 + \Delta d_{m2})^2$ instead of d_1 : $\xi_2 = \sum_{m=3}^M ((\mathbf{p}_m - \mathbf{p}_2)^T \mathbf{p} + \Delta d_{m2}d_2 - b_{2m})^2 = \|\mathbf{e}_2\|^2$ where $b_{2m} = \frac{\|\mathbf{p}_m\|^2 - \|\mathbf{p}_2\|^2 - \Delta d_{m2}^2}{2}$, $3 \leq m \leq M$

- \dots and the $(M-2) \times 1$ error vector \mathbf{e}_2 is given as

$$\mathbf{e}_2 = \begin{bmatrix} (\mathbf{p}_3 - \mathbf{p}_2)^T & \Delta d_{32} \\ \vdots & \vdots \\ (\mathbf{p}_M - \mathbf{p}_2)^T & \Delta d_{M2} \end{bmatrix} \begin{bmatrix} \mathbf{p} \\ d_2 \end{bmatrix} - \begin{bmatrix} b_{23} \\ \vdots \\ b_{2M} \end{bmatrix}$$

- Similarly, we do the same for d_3 to d_{M-1} defining matrices \mathbf{A}_3 to \mathbf{A}_{M-1} and vectors \mathbf{b}_3 to \mathbf{b}_{M-1}

The Extended Solution

- The extended cost function is formed using all N TDOAs measurements:

$$\xi = \sum_{m=1}^M \xi_m,$$

where $\xi_m = \mathbf{e}_m^T \mathbf{e}_m$, and $\mathbf{e}_m = \mathbf{A}_m [\mathbf{p}^T \ d_m]^T - \mathbf{b}_m$

- From the definitions of ξ_m , \mathbf{e}_m and \mathbf{A}_m , the extended cost function can be expressed as $\xi = \mathbf{e}^T \mathbf{e}$, where

$$\begin{bmatrix} (\mathbf{p}_2 - \mathbf{p}_1)^T & \Delta d_{21} & 0 & 0 \cdots 0 \\ \vdots & \vdots & \vdots & \vdots \\ (\mathbf{p}_M - \mathbf{p}_1)^T & \Delta d_{M1} & 0 & 0 \cdots 0 \\ (\mathbf{p}_3 - \mathbf{p}_2)^T & 0 & \Delta d_{32} & 0 \cdots 0 \\ \vdots & \vdots & \vdots & \vdots \\ (\mathbf{p}_M - \mathbf{p}_2)^T & 0 & \Delta d_{M2} & 0 \cdots 0 \\ \vdots & \vdots & \vdots & \vdots \\ (\mathbf{p}_M - \mathbf{p}_{M-1})^T & 0 & 0 & \cdots 0 \Delta d_{M(M-1)} \end{bmatrix} \begin{bmatrix} \mathbf{p} \\ d_1 \\ d_2 \\ \vdots \\ d_{M-1} \end{bmatrix} - \begin{bmatrix} \mathbf{b}_1 \\ \mathbf{b}_2 \\ \vdots \\ \mathbf{b}_{M-1} \end{bmatrix}$$

- Such that the extended LS solution is given by $[\hat{\mathbf{p}}^T \ \hat{d}_1 \ \hat{d}_2 \ \cdots \ \hat{d}_{M-1}]^T = (\mathbf{A}^T \mathbf{A})^{-1} \mathbf{A}^T \mathbf{b}$

The Proposed Algorithm

Let \mathbf{p}_m , $1 \leq m \leq M$, be the positions of M sensors
 $N \leftarrow \frac{M(M-1)}{2}$
 Let τ_{ij} be the N available TDOAs (in # samples)
 Set v and f_s , and choose n
 $\Delta d_{ij} \leftarrow \frac{v\tau_{ij}}{f_s}$ for all N TDOAs
 $|\Delta d_{ij}|_{\max} \leftarrow \|\mathbf{p}_i - \mathbf{p}_j\|$ for all N TDOAs
 Form matrix \mathbf{A} and vector \mathbf{b}
 $\hat{\mathbf{p}}_n \leftarrow [\mathbf{I} \ \mathbf{0}] (\mathbf{A}^T \mathbf{A})^{-1} \mathbf{A}^T \mathbf{b}$
 $\hat{d}_m \leftarrow \|\hat{\mathbf{p}}_n - \mathbf{p}_m\|$ for all $1 \leq m \leq M$ sensors
 $\Delta \hat{d}_{ij} \leftarrow \hat{d}_i - \hat{d}_j$ for all N possible pairs $\{i, j\}$
 $\xi_{\min} \leftarrow \frac{1}{N} \sum_{\{i,j\}} (\Delta \hat{d}_{ij} - \Delta d_{ij})^2$
 for each subset of measurements \mathcal{S}_n
 if all $\{|\Delta d_{ij}| \leq |\Delta d_{ij}|_{\max}, \{i, j\} \in \mathcal{S}_n\}$
 do
 then
 Adjust \mathbf{A}_n and \mathbf{b}_n according to \mathcal{S}_n
 $\hat{\mathbf{p}}_n \leftarrow [\mathbf{I} \ \mathbf{0}] (\mathbf{A}_n^T \mathbf{A}_n)^{-1} \mathbf{A}_n^T \mathbf{b}_n$
 $\hat{d}_m \leftarrow \|\hat{\mathbf{p}}_n - \mathbf{p}_m\|$ for $1 \leq m \leq M$
 $\Delta \hat{d}_{ij} \leftarrow \hat{d}_i - \hat{d}_j$ for $\{i, j\} \in \mathcal{S}_n$
 $\xi_n \leftarrow \frac{1}{n} \sum_{\{i,j\} \in \mathcal{S}_n} (\Delta \hat{d}_{ij} - \Delta d_{ij})^2$
 if $\xi_n < \xi_{\min}$
 then $\xi_{\min} \leftarrow \xi_n$
 $\mathbf{p}_o \leftarrow \hat{\mathbf{p}}_n$
 return (\mathbf{p}_o)

Experimental Results

TNR / # outliers	Geometry	Conv. LS	Ext. LS	DS-LS
10dB / 3	1	4.1885	4.0103	1.3808
	2	5.4328	3.5410	0.3731
20dB / 2	1	2.1831	2.2836	0.1312
	2	2.2328	1.7517	0.1073
30dB / 1	1	0.8383	0.9316	0.0355
	2	0.5861	0.5022	0.0337
40dB / 0	1	0.0140	0.0095	0.0110
	2	0.0108	0.0065	0.0108

$$TNR = 10 \log \left(\frac{\frac{1}{N} \sum_{ij} \tau_{ij}^2}{\sigma_{TDOA}^2} \right)$$

Conclusions

- DS is effective in TDOA-based localization
- The algorithm is more successful for noisy and reverberant scenarios

