

Semidefinite Relaxation Method for Moving Object Localization Using A Stationary Transmitter at Unknown Position

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Introduction

- Background

- Multistatic localization becomes a popular research topic as it finds applications in target tracking, automatic driving, robotics, and many others.
- The information of time-delay (TD), differential-arrival-times, Doppler-frequency-shift (DFS) can be used.

- Unknown Transmitter Position

- The transmitter may be located somewhere in which the GPS is not accessible.
- It could happen in the passive coherent location (PCL) systems, where an existing facility is used as the transmitter.
- The transmitter position can even be intentionally left unknown for lower hardware and implementation costs.

- Existing Methods

- Methods based on TD measurements only:
Two-step weighted least-squares (TSWLS) and Semidefinite relaxation (SDR).
- Method based on TD and DFS measurements: TSWLS.

- Contribution

- We propose an accurate SDR method for estimating the object position and velocity when the transmitter position is unknown.

Introduction

- Illustration of the localization scenario

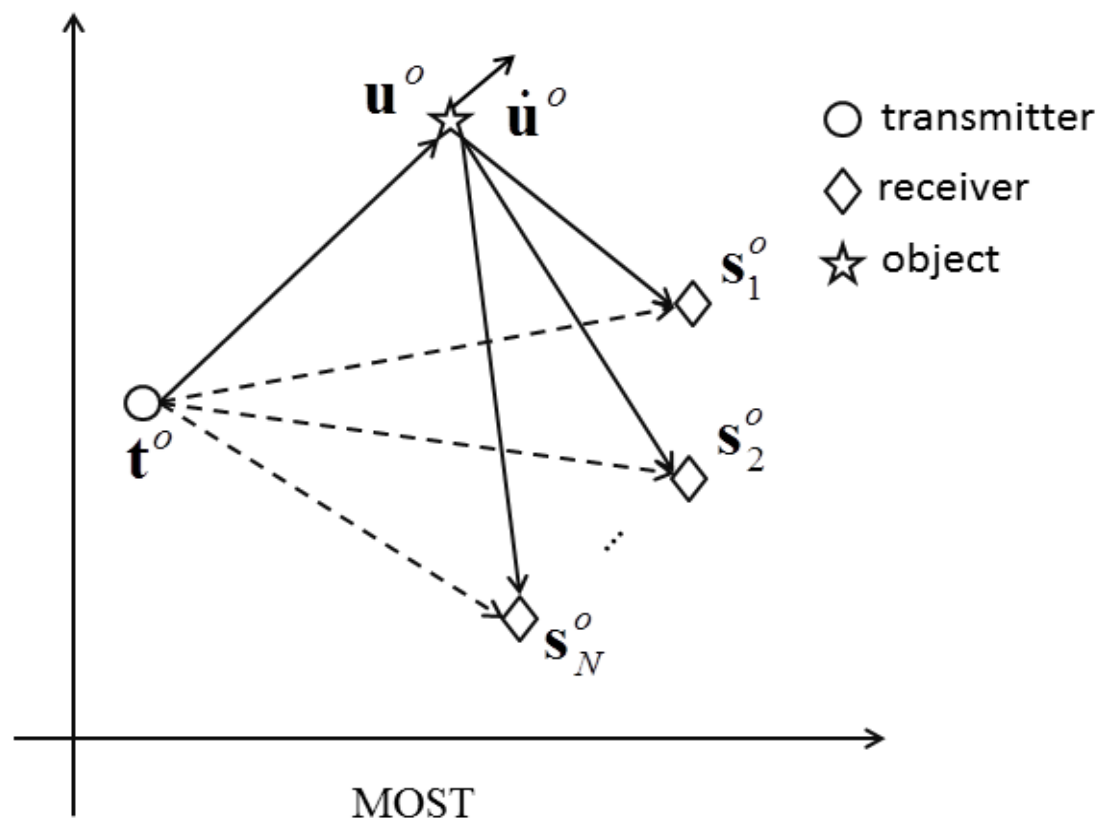


Figure 1: Illustration of the localization scenario of moving object and stationary transmitter (MOST): **Receivers are synchronized.**

Measurement Model

- The true ranges in the indirect and direct paths can be expressed as

$$\begin{aligned} r_j^o &= \|\mathbf{u}^o - \mathbf{s}_j^o\| + \|\mathbf{u}^o - \mathbf{t}^o\| + b_\tau^o, \quad j = 1, \dots, N, \\ d_j^o &= \|\mathbf{s}_j^o - \mathbf{t}^o\| + b_\tau^o, \quad j = 1, \dots, N. \end{aligned} \quad (1)$$

where

- \mathbf{u}^o and $\dot{\mathbf{u}}^o$: object position and velocity, respectively (unknown);
 - \mathbf{t}^o : transmitter position (unknown);
 - \mathbf{s}_j^o : j -th receiver position (known);
 - b_τ^o time offset at the transmitter (unknown).
- The true range rates, which are transformed from the DFS, in the indirect and direct paths are:

$$\begin{aligned} \dot{r}_j^o &= \boldsymbol{\rho}_{\mathbf{u}^o - \mathbf{s}_j^o}^T \dot{\mathbf{u}}^o + \boldsymbol{\rho}_{\mathbf{u}^o - \mathbf{t}^o}^T \dot{\mathbf{u}}^o + b_f^o, \quad j = 1, \dots, N, \\ \dot{d}_j^o &= b_f^o, \quad j = 1, \dots, N, \end{aligned} \quad (2)$$

where b_f^o is the unknown frequency offset.

Measurement Model

- In practice, the measurements observed by the receiver are contaminated by noise, i.e.,

$$\begin{aligned}r_j &= r_j^o + \varepsilon_{r,j}, \quad j = 1, \dots, N, \\d_j &= d_j^o + \varepsilon_{d,j}, \quad j = 1, \dots, N, \\\dot{r}_j &= \dot{r}_j^o + \dot{\varepsilon}_{\dot{r},j}, \quad j = 1, \dots, N, \\\dot{d}_j &= \dot{d}_j^o + \dot{\varepsilon}_{\dot{d},j}, \quad j = 1, \dots, N,\end{aligned}\tag{3}$$

where $\varepsilon_{r,j}$, $\dot{\varepsilon}_{\dot{r},j}$, $\varepsilon_{d,j}$, and $\dot{\varepsilon}_{\dot{d},j}$ are the additive noise.

Problem Formulation

- Dealing with the indirect path models.

Transforming the indirect path range measurement model gives

$$\begin{aligned} & \frac{1}{2}(r_j^2 - \|\mathbf{s}_j^o\|^2) + \mathbf{s}_j^{oT} \mathbf{u}^o - r_j \rho^o - r_j b_\tau^o - \frac{1}{2} \varphi_1^o \\ & = \|\mathbf{u}^o - \mathbf{s}_j^o\| \varepsilon_{r,j}, \quad j = 1, \dots, N, \end{aligned} \quad (4)$$

where $\varphi_1^o = \|\mathbf{u}^o\|^2 - \rho^{o2} - 2\rho^o b_\tau^o - b_\tau^{o2}$, $\rho^o = \|\mathbf{u}^o - \mathbf{t}^o\|$, and the second-order noise terms $\varepsilon_{r,j}^2$ are neglected.

The equation for range rate is obtained based on time-derivative of (4) and incorporating the frequency offset,

$$\begin{aligned} & r_j \dot{r}_j + \mathbf{s}_j^{oT} \dot{\mathbf{u}}^o - \dot{r}_j \rho^o - r_j \dot{\rho}^o - \dot{r}_j b_\tau^o - r_j b_f^o - \varphi_2^o \\ & = \boldsymbol{\rho}_{\mathbf{u}^o - \mathbf{s}_j^o}^T \dot{\mathbf{u}}^o \varepsilon_{r,j} + \|\mathbf{u}^o - \mathbf{s}_j^o\| \dot{\varepsilon}_{r,j}, \quad j = 1, \dots, N, \end{aligned} \quad (5)$$

where $\dot{\rho}^o = \boldsymbol{\rho}_{\mathbf{u}^o - \mathbf{t}^o}^T \dot{\mathbf{u}}^o$ and $\varphi_2^o = \mathbf{u}^{oT} \dot{\mathbf{u}}^o - \rho^o \dot{\rho}^o - \dot{\rho}^o b_\tau^o - \rho^o b_f^o - b_\tau^o b_f^o$.

- Dealing with the direct path models. The direct path range measurement model can be manipulated similarly and approximated by

$$\begin{aligned} \frac{1}{2}(d_j^2 - \|\mathbf{s}_j^o\|^2) + \mathbf{s}_j^{oT} \mathbf{t}^o - d_j b_\tau^o - \frac{1}{2} \varphi_3^o &= \|\mathbf{t}^o - \mathbf{s}_j^o\| \varepsilon_{d,j}, \\ j &= 1, \dots, N, \end{aligned} \quad (6)$$

where $\varphi_3^o = \|\mathbf{t}^o\|^2 - b_\tau^{o2}$.

The frequency offset is present in the direct path DFS observations

$$\dot{d}_j = b_f^o + \varepsilon_{\dot{d},j}, \quad j = 1, \dots, N. \quad (7)$$

Problem Formulation

- Define the unknown vector \mathbf{y}^o :

$$\mathbf{y}^o = [\underbrace{\mathbf{u}^{oT}}_{1 \times k}, \underbrace{\dot{\mathbf{u}}^{oT}}_{1 \times k}, \underbrace{\mathbf{t}^{oT}}_{1 \times k}, \underbrace{b_\tau^o}_1, \underbrace{b_f^o}_1, \underbrace{\rho^o}_1, \underbrace{\dot{\rho}^o}_1, \underbrace{\varphi_1^o}_1, \underbrace{\varphi_2^o}_1, \underbrace{\varphi_3^o}_1]^T.$$

Using \mathbf{y}^o , we can express the pseudo-linear equations in (4), (5), (6), and (7) as the following matrix forms:

$$\mathbf{b}_r - \mathbf{A}_r \mathbf{y}^o \simeq \mathbf{B}_r \boldsymbol{\varepsilon}_r, \quad (8a)$$

$$\mathbf{b}_{\dot{r}} - \mathbf{A}_{\dot{r}} \mathbf{y}^o \simeq \mathbf{B}_{\dot{r}} \boldsymbol{\varepsilon}_r + \mathbf{B}_r \dot{\boldsymbol{\varepsilon}}_r, \quad (8b)$$

$$\mathbf{b}_d - \mathbf{A}_d \mathbf{y}^o \simeq \mathbf{B}_d \boldsymbol{\varepsilon}_d, \quad (8c)$$

$$\mathbf{b}_{\dot{d}} - \mathbf{A}_{\dot{d}} \mathbf{y}^o = \dot{\boldsymbol{\varepsilon}}_d. \quad (8d)$$

Combining the approximate equations in (8a)-(8d) yields

$$\mathbf{b} - \mathbf{A} \mathbf{y}^o \simeq \mathbf{B} \boldsymbol{\varepsilon}. \quad (9)$$

Problem Formulation

- Base on (9), we can formulate a WLS problem to estimate \mathbf{y}^o :

$$\min_{\mathbf{y}} (\mathbf{b} - \mathbf{A}\mathbf{y})^T \Sigma^{-1} (\mathbf{b} - \mathbf{A}\mathbf{y}), \quad (10a)$$

$$\text{s.t. } y_{(3k+3)}^2 = \|\mathbf{y}_{(1:k)} - \mathbf{y}_{((2k+1):3k)}\|^2, \quad (10b)$$

$$y_{(3k+4)} = \frac{(\mathbf{y}_{(1:k)} - \mathbf{y}_{((2k+1):3k)})^T}{\|\mathbf{y}_{(1:k)} - \mathbf{y}_{((2k+1):3k)}\|} \mathbf{y}_{((k+1):2k)}, \quad (10c)$$

$$y_{(3k+3)} y_{(3k+4)} = (\mathbf{y}_{(1:k)} - \mathbf{y}_{((2k+1):3k)})^T \mathbf{y}_{((k+1):2k)}, \quad (10d)$$

$$y_{(3k+5)} = \|\mathbf{y}_{(1:k)}\|^2 - (y_{(3k+3)} + y_{(3k+1)})^2, \quad (10e)$$

$$\begin{aligned} y_{(3k+6)} = & -(y_{(3k+1)} + y_{(3k+3)})(y_{(3k+2)} + y_{(3k+4)}) \\ & + \mathbf{y}_{(1:k)}^T \mathbf{y}_{(k+1:2k)}, \end{aligned} \quad (10f)$$

$$y_{(3k+7)} = \|\mathbf{y}_{((2k+1):3k)}\|^2 - y_{(3k+1)}^2, \quad (10g)$$

where $\Sigma = \mathbf{BQB}^T$.

- Let $\mathbf{Y} = \mathbf{y}\mathbf{y}^T$. Problem (10) can be relaxed into the following semidefinite program (SDP) by dropping the $\text{rank}(\mathbf{Y}) = 1$ constraint:

$$\min_{\mathbf{y}} \quad \text{tr} \left\{ \begin{bmatrix} \mathbf{Y} & \mathbf{y} \\ \mathbf{y}^T & 1 \end{bmatrix} \begin{bmatrix} \mathbf{A}^T \Sigma^{-1} \mathbf{A} & -\mathbf{A}^T \Sigma^{-1} \mathbf{b} \\ -\mathbf{b}^T \Sigma^{-1} \mathbf{A} & \mathbf{b}^T \Sigma^{-1} \mathbf{b} \end{bmatrix} \right\}, \quad (11a)$$

$$\begin{aligned} \text{s.t. } Y_{(3k+3,3k+3)} &= \text{tr}\{\mathbf{Y}_{(1:k,1:k)}\} - 2\text{tr}\{\mathbf{Y}_{(1:k,(2k+1):3k)}\} \\ &\quad + \text{tr}\{\mathbf{Y}_{((2k+1):3k,(2k+1):3k)}\}, \end{aligned} \quad (11b)$$

$$Y_{(3k+3,3k+4)} = \text{tr}\{\mathbf{Y}_{(1:k,(k+1):2k)}\} - \text{tr}\{\mathbf{Y}_{((2k+1):3k,(k+1):2k)}\}, \quad (11c)$$

$$\begin{aligned} y_{(3k+5)} &= \text{tr}\{\mathbf{Y}_{(1:k,1:k)}\} - Y_{(3k+3,3k+3)} - 2Y_{(3k+1,3k+3)} \\ &\quad - Y_{(3k+1,3k+1)}, \end{aligned} \quad (11d)$$

$$\begin{aligned} y_{(3k+6)} &= \text{tr}\{\mathbf{Y}_{(1:k,k+1:2k)}\} - Y_{(3k+3,3k+4)} \\ &\quad - Y_{(3k+1,3k+4)} - Y_{(3k+3,3k+2)} - Y_{(3k+1,3k+2)}, \end{aligned} \quad (11e)$$

$$y_{(3k+7)} = \text{tr}\{\mathbf{Y}_{(2k+1:3k,2k+1:3k)}\} - Y_{(3k+1,3k+1)}, \quad (11f)$$

$$Y_{(3k+4,3k+4)} \leq \text{tr}\{\mathbf{Y}_{((k+1):2k,(k+1):2k)}\}, \quad (11g)$$

$$\begin{bmatrix} \mathbf{Y} & \mathbf{y} \\ \mathbf{y}^T & 1 \end{bmatrix} \succeq \mathbf{0}. \quad (11h)$$

Simulations

- Parameter Setup

- Transmitter and receiver positions: randomly selected in the 3-D space of size $(-4000, 4000) \times (-4000, 4000) \times (1000, 3000) \text{ m}^3$.
- Object position and velocity: $\mathbf{u}^o = [-1000, 500, 1500]^T \text{ m}$, $\dot{\mathbf{u}}^o = [15, 15, 30]^T \text{ m/s}$.
- Unknown time and frequency offsets: $b_\tau^o = 200 \text{ m}$, $b_f^o = 5 \text{ m/s}$.
- Covariance matrix: $\mathbf{Q} = \text{blkdiag}(\mathbf{Q}_r, \mathbf{Q}_{\dot{r}}, \mathbf{Q}_d, \mathbf{Q}_{\dot{d}})$, $\mathbf{Q}_{\dot{r}} = 0.1\mathbf{Q}_r$ and $\mathbf{Q}_{\dot{d}} = 0.1\mathbf{Q}_d$.
- MSE: $\text{MSE}(\hat{\boldsymbol{\zeta}}) = \frac{1}{KL} \sum_{j=1}^K \sum_{i=1}^L \|\hat{\boldsymbol{\zeta}}_{ji} - \boldsymbol{\zeta}_j^o\|^2$,
where $\hat{\boldsymbol{\zeta}}_{ji}$ is the estimate of the true value $\boldsymbol{\zeta}_j^o$ in the i -th Monte Carlo (MC) run for the j -th configuration. K and L are the numbers of configurations and MC runs, respectively. Set $K = 10$ and $L = 1000$.

Simulations

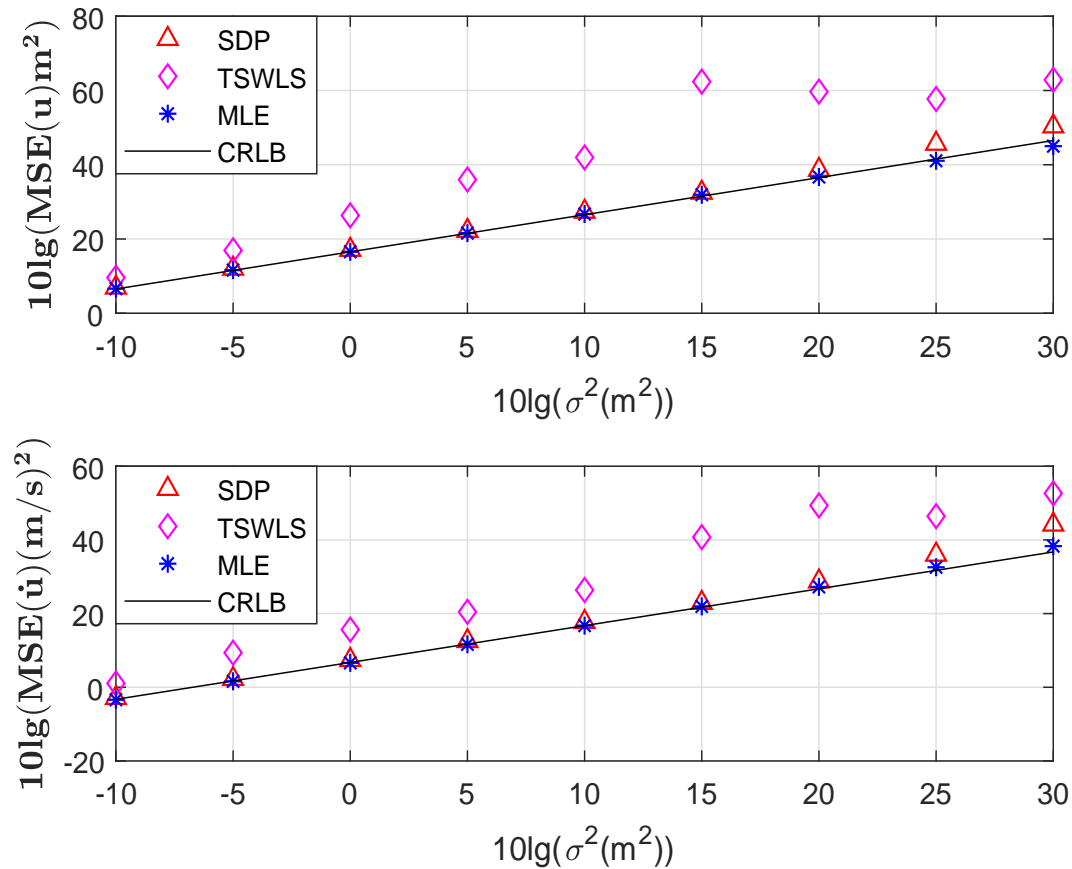


Figure 2: MSE comparison for 3-D localization: ten randomly generated configurations each with one transmitter and **five receivers**.

Simulations

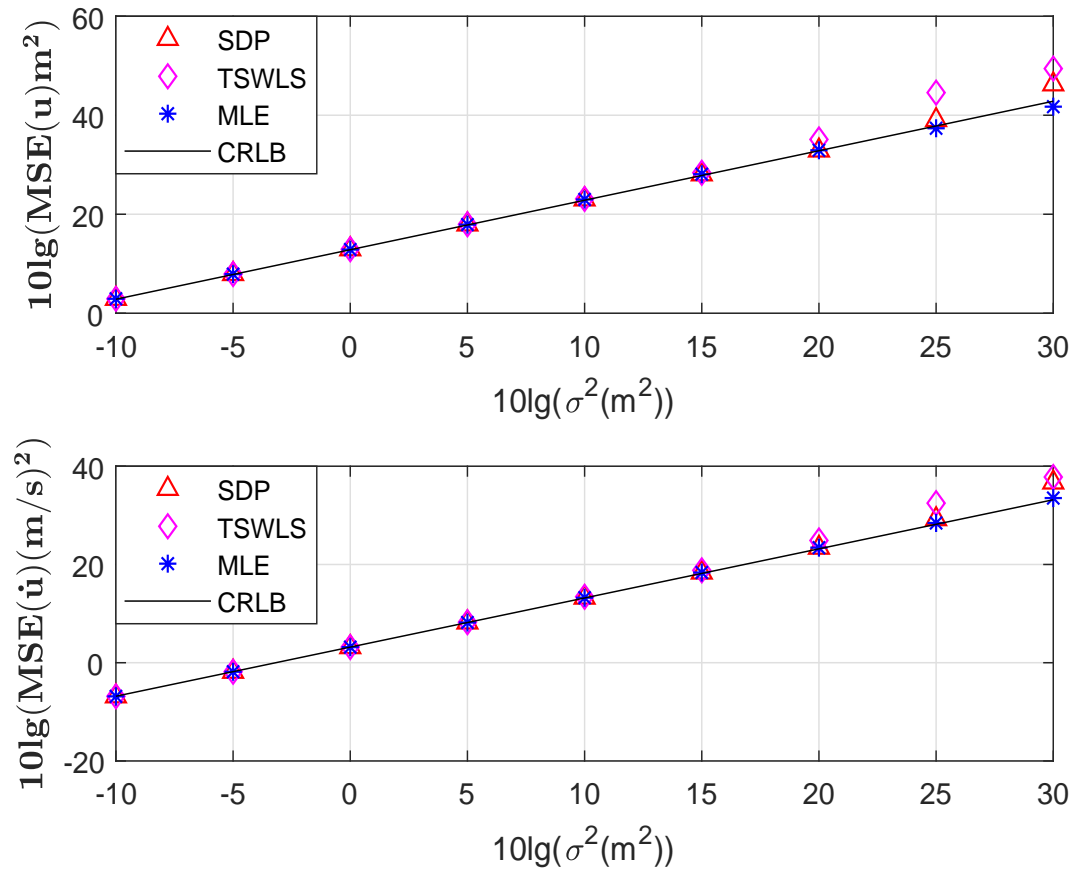


Figure 3: MSE comparison for 3-D localization: ten randomly generated configurations each with one transmitter and **six receivers**.

Simulations

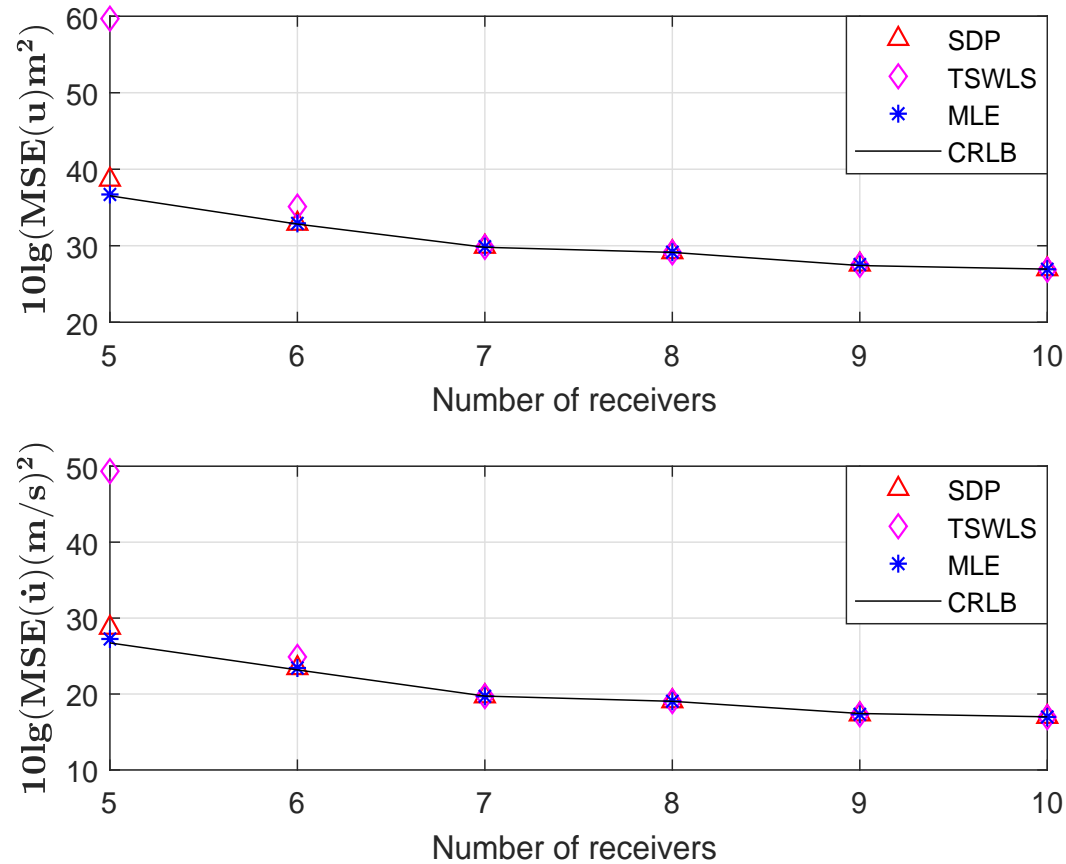


Figure 4: MSE comparison for 3-D localization at $\sigma = 10$ m as the number of receivers varies: ten randomly generated configurations.

Thank You