HIGH RESOLUTION LOCATION IN ULTRA WIDEBAND COMMUNICATIONS SYSTEMS

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Abstract

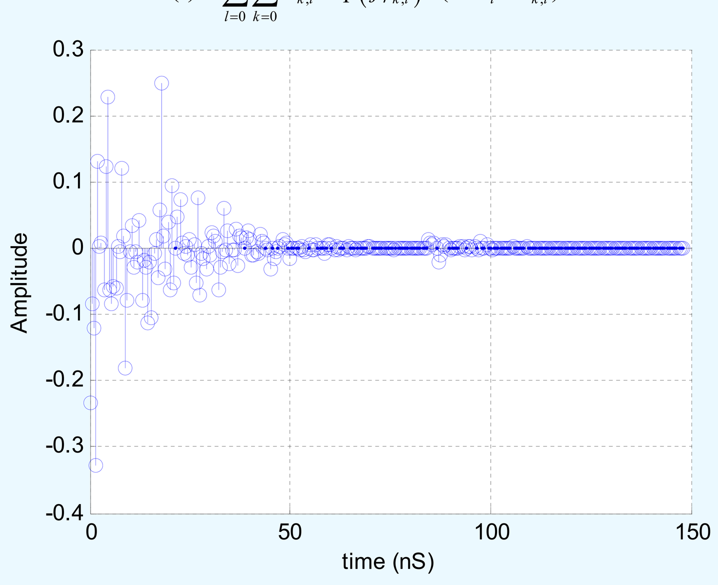
- Ultra Wideband (UWB) communications systems provide high accuracy positioning estimation because the high multipath resolution capacity.
- This paper deals with the Normalized Minimum Variance (NMV) technique for estimating Time Of Arrival (TOA) exploiting the pulse train defined in the Impulse Radio (IR) transmission.
- Positioning estimation is tackled with the Extended Kalman Filter (EKF) with TOA bias tracking allowing high accuracy even in Non Line Of Sight (NLOS) scenarios

Conclusions

- In this paper the potentiality of the UWB communications systems for ranging and positioning applications has been presented.
- Different ranging methods based on NMV TOA estimation exploiting the pulse train defined in the IR transmission have been proposed and evaluated in LOS and NLOS scenarios. It can be concluded that the method based on the minimum TOA estimated provides high ranging accuracy.
- From ranging measurements, the proposed EKF with TOA bias tracking improves significantly the performance of the location estimation in NLOS scenarios.

Propagation Channel Model

$$h(t)=\sum_{l=0}^{L}\sum_{k=0}^{K}\alpha_{k,l}\exp\left(j\phi_{k,l}\right)\delta\left(t-T_l-\tau_{k,l}\right)$$



The signal model assumed for the estimated channel collected over N time instants is:

$$y(\tau;n)=\sum_{i=1}^{L}a_i(n)g(\tau-\tau_i)+v(\tau;n) \qquad n=1,\ldots,N$$

Path amplitud — Pulse shaping

DFT

$$y(\omega;n)=\sum_{i=1}^{L}a_i(n)g(\omega)e^{j\omega\tau_i}+v(\omega;n)$$

Stacking the samples of the transformed domain in a single vector:

$$\mathbf{y}(n)=\begin{bmatrix}y(\omega_0;n)\\ y(\omega_1;n)\\ \vdots\\ y(\omega_{M-1};n)\end{bmatrix}=\sum_{i=1}^{L}a_i(n)\mathbf{G}\mathbf{e}_{\tau_i}+\mathbf{v}(n)=\mathbf{G}\mathbf{E}_{\tau_i}\mathbf{a}(n)+\mathbf{v}(n)$$

DFT of the pulse shaping filter

- Simple algorithms like early-late exhibit bad performance in multipath channels
- ML estimates ⇒ complex multidimensional search.

Reduced complexity techniques require:

- Previous knowledge of the number of paths (L) to be estimated (i.e. root-MUSIC, ESPRIT).
- SVD decomposition (i.e. root-MUSIC, ESPRIT)
- Time incoherence of the incoming rays (i.e. MV, root-MUSIC)
- One-dimensional grid search (i.e. root-MUSIC, MV)

Minimum Variance (MV) timing estimation

Reduction of the complexity by considering signals separation through filtering

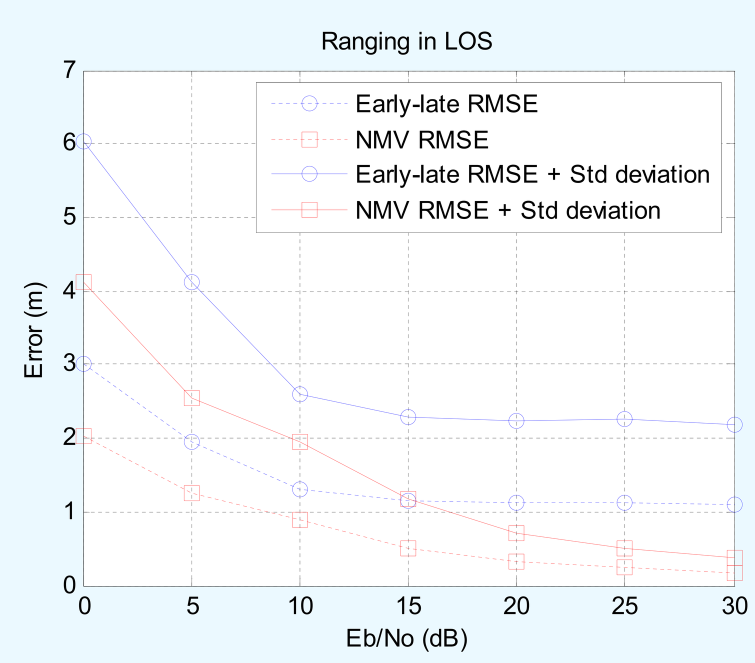
$$\mathbf{y}(n)=a_j(n)\mathbf{G}\mathbf{e}_{\tau_j}+\mathbf{v}(n)$$

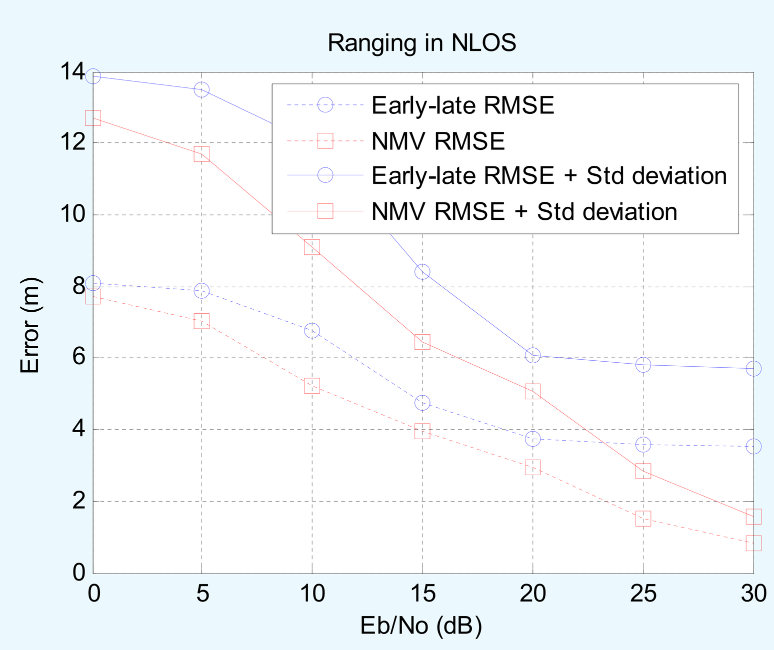
Single path of interest — Channel noise plus the non considered paths

MV filter output: $\mathbf{z}(n)=\mathbf{w}^H\mathbf{y}(n)=a_j(n)\mathbf{w}^H\mathbf{G}\mathbf{e}_{\tau_j}+\mathbf{w}^H\mathbf{v}(n)$

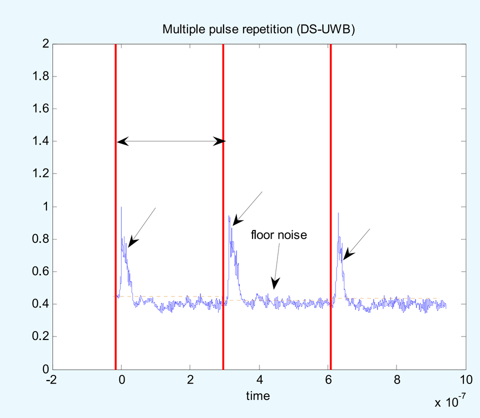
To maximise $SNR=\dfrac{E\left\{\left|a_j(n)\right|^2\right\}}{\mathbf{w}^H E\left\{\mathbf{v}(n)\mathbf{v}(n)^H\right\}\mathbf{w}}$ subject to: $\mathbf{w}^H\mathbf{G}\mathbf{e}_{\tau_j}=1$

MV solution	Power delay spectrum
$\mathbf{w}(\tau)=\dfrac{\mathbf{R}_y^{-1}\mathbf{G}\mathbf{e}_\tau}{\mathbf{e}_\tau^H\mathbf{G}^H\mathbf{R}_y^{-1}\mathbf{G}\mathbf{e}_\tau}$	$P(\tau)=\dfrac{1}{\mathbf{e}_\tau^H\mathbf{G}^H\mathbf{R}_y^{-1}\mathbf{G}\mathbf{e}_\tau}$





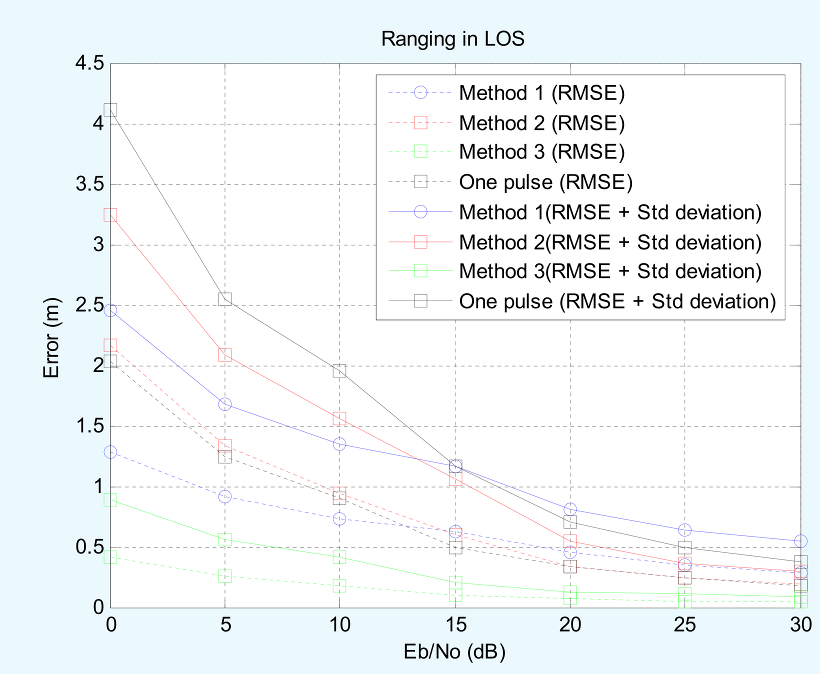
IR UWB TOA ESTIMATION

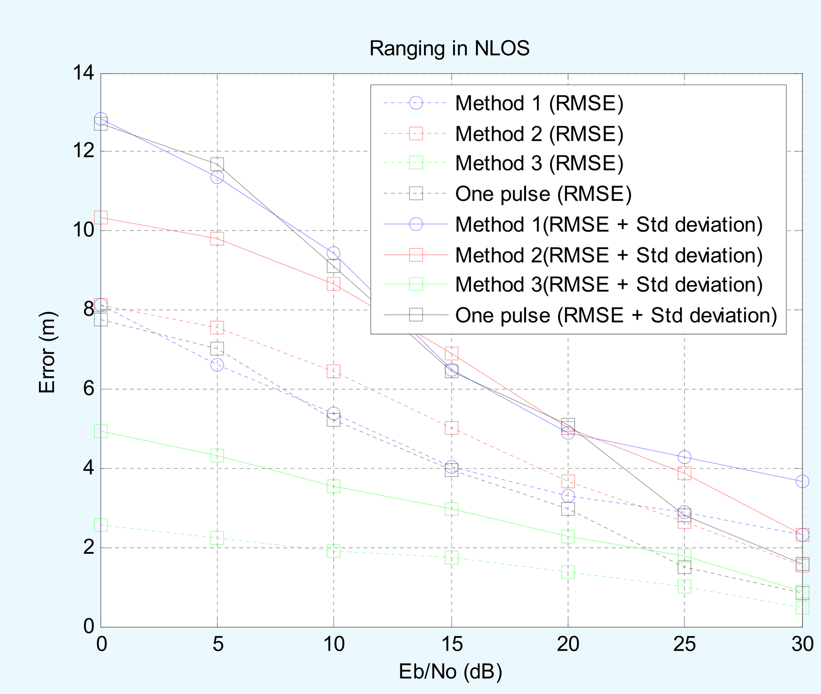


Method 1: Maximum energy. $E_{max}=\max\left\{\sum_{j=1}^{N_p}S_j(\tau_1),\ \sum_{j=1}^{N_p}S_j(\tau_2),\ \ldots,\ \sum_{j=1}^{N_p}S_j\left(\tau_{N_p}\right)\right\}$

Method 2: Mean $\tau_{mean}=\dfrac{1}{N}\sum_{i=1}^{N}\tau_i$

Method 3: Minimum $\tau_{min}=\min\{\tau_1,\tau_2,\ldots,\tau_N\}$





Kalman Positioning Tracker

Transition equation: $\mathbf{s}'(k+1)=\mathbf{D}\mathbf{s}'(k)+\mathbf{w}(k)$

Dynamic State vector — State matrix — Noise vector

$$\mathbf{s}'(k)=\begin{bmatrix}\mathbf{s}(k)\\ \mathbf{b}(k)\end{bmatrix} \qquad \mathbf{D}=\begin{bmatrix}\mathbf{A} & \mathbf{0}\\ \mathbf{0} & \mathbf{B}\end{bmatrix} \qquad \mathbf{w}(k)=\begin{bmatrix}\mathbf{0} & \mathbf{w}_v & \mathbf{w}_b\end{bmatrix}^T$$

Measurement equation: $\mathbf{z}(k)=g\left(\mathbf{s}(k)\right)+\mathbf{b}(k)+\mathbf{v}(k) \longrightarrow \mathbf{z}(k)=\mathbf{J}(k)^H\mathbf{s}'(k)+\mathbf{v}(k)$

Extended Kalman Filter $\mathbf{G}(k)=\left.\dfrac{\partial g}{\partial \mathbf{s}}\right|_{\mathbf{s}=\hat{\mathbf{s}}(k/k-1)}=\mathbf{F}(k)/c \longrightarrow \mathbf{J}(k)^H=\begin{bmatrix}\mathbf{G}(k) & \mathbf{I}\end{bmatrix}$

State vector prediction equal to the conditioned mean:

$$\hat{\mathbf{s}}(k/k-1)=E\{\mathbf{s}(k)|\mathbf{z}(k-1)\}$$

$$\mathbf{F}(k)=\begin{bmatrix}\left(\hat{\mathbf{s}}(k-1)-\mathbf{r}_1\right)/d_1(k-1)\\ \ldots\\ \left(\hat{\mathbf{s}}(k-1)-\mathbf{r}_N\right)/d_N(k-1)\end{bmatrix}$$

$\hat{\mathbf{s}}$(k-1) MS position vector estimated at the previous algorithm iteration

$\mathbf{r}_i$ Location of the i-th BS.

$d_i(k-1)=\left\|\hat{\mathbf{s}}(k-1)-\mathbf{r}_i\right\|$

Mean Square Error is the trace of the error covariance matrix:

$$\boldsymbol{\Sigma}(k/k-1)=E\left\{\left|\left(\mathbf{s}'(k)-\hat{\mathbf{s}}'(k/k-1)\right)\right|^2/\mathbf{z}(k-1)\right\}$$

Time update equations:

$$\hat{\mathbf{s}}'(k+1/k)=\mathbf{D}\hat{\mathbf{s}}'(k/k)$$
$$\boldsymbol{\Sigma}(k+1/k)=\mathbf{D}\boldsymbol{\Sigma}(k/k-1)\mathbf{D}^H+\mathbf{Q}$$

Measurement update equations:

$$\hat{\mathbf{s}}'(k/k)=\hat{\mathbf{s}}'(k/k-1)+\mathbf{K}(k)\left[\mathbf{z}(k)-g\left(\hat{\mathbf{s}}(k/k-1)\right)-\hat{\mathbf{b}}(k/k-1)\right]$$
$$\boldsymbol{\Sigma}(k/k)=\left[\mathbf{I}-\mathbf{K}(k)\mathbf{J}(k)^H\right]\boldsymbol{\Sigma}(k/k-1)$$

Kalman gain matrix:

$$\mathbf{K}(k)=\boldsymbol{\Sigma}(k/k-1)\mathbf{J}(k)\left[\mathbf{J}(k)^H\boldsymbol{\Sigma}(k/k-1)\mathbf{J}(k)+\mathbf{C}(k)\right]^{-1}$$