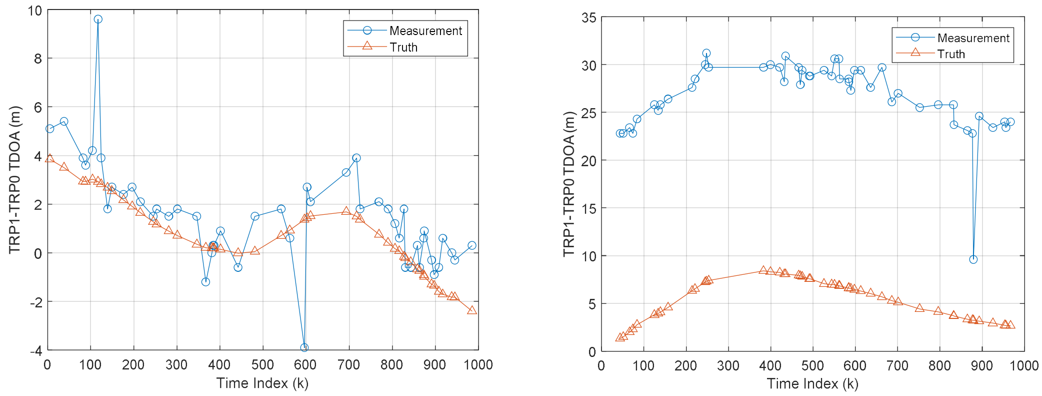
In the IPIN competition 2022 Track 8, two sets of data are given to calibrate the algorithmic models, namely Testing_Trial_A, and Testing_Trial_B. Each set contains 1000 measurements (~85seconds long) with 50 ground-truth positions. In each set, the TOA measurements and RSRP measurements are provided to achieve accurate positioning of the terminal.

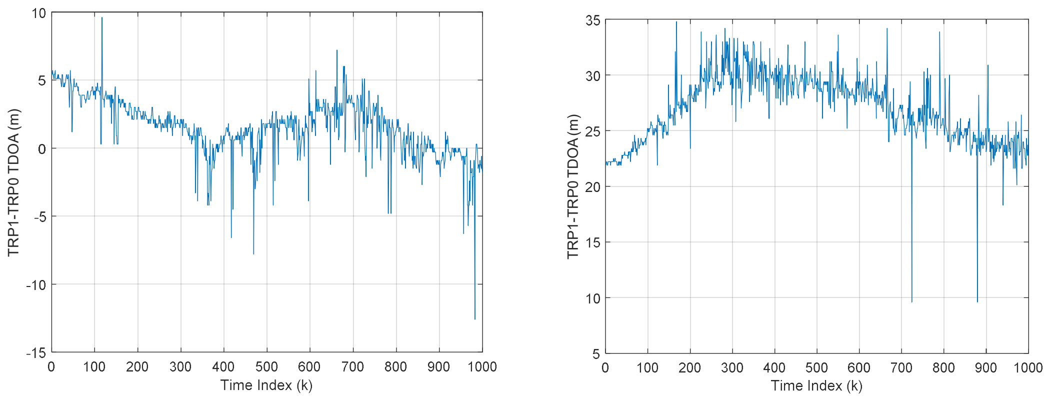
Note that there are unknown timing errors among the receivers in TRPs, called time alignment errors (TAEs). For example, Fig.1 shows the TDOA of the TRP0 and TRP1 for these two datasets at 50 ground-truth positions. For the Testing_Trial_A, the TAE of the TRP0 and TRP1 is 0.8m. For the Testing_Trial_B, the TAE of the TRP0 and TRP1 is 21.3m. As shown in Fig.1 the TAEs are kept constant in a dataset but are different between different datasets. Therefore, a key challenge to realize high-precision positioning is to estimate the TAEs accurately.



(a) Testing_Trial_A (b) Testing_Trial_B

Fig.1 TDOA of the TRP0 and TRP1 at 50 ground-truth positions

In addition, since the indoor environment is very complex, there may exist a mixture of LOS paths, weak LOS paths, NLOS paths. For example, Fig.2 shows the TDOA of the TRP0 and TRP1 for these two datasets. As shown in Fig.2, there are a lot of outliers in the TDOA measurements which are caused by the weak LOS paths and NLOS paths. Obviously, in order to achieve high-precision positioning, the outliers must be handled reasonably.



(a) Testing_Trial_A (b) Testing_Trial_B

Fig.2 TDOA of the TRP0 and TRP1

In a word, to realize high-precision positioning, the TAEs should be estimated accurately and the outliers must be handled reasonably. For the TAEs estimation, the RSRP measurements are employed. The relationship between RSRP and TOA can generally be expressed as

$$\rho = A - 10\eta \log\left(d\right) + \varepsilon \tag{1}$$

where ρ is the RSRP measurement, d is the distance between terminal and TRP, A and η are the model parameters which can be determined by using the datasets, ε is the measurement noise. In this manuscript, the extended Kalman filter (EKF) is employed to estimate the TAEs and the location of the terminal simultaneously. The state space model for the TAEs and location estimation can be written as

$$\begin{aligned} \boldsymbol{x}_k &= \boldsymbol{F}_{k-1}\boldsymbol{x}_{k-1} + \boldsymbol{G}_{k-1}\boldsymbol{w}_{k-1} \\ \boldsymbol{z}_k &= \boldsymbol{h}\left(\boldsymbol{x}_k\right) + \boldsymbol{v}_k \end{aligned} \tag{2}$$

$$\boldsymbol{F}_{k-1} = \begin{bmatrix} 1 & T & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & T & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{3}$$

$$\boldsymbol{G}_{k-1} = \begin{bmatrix} T^2/2 & 0 & 0 & 0 & 0 \\ T & 0 & 0 & 0 & 0 \\ 0 & T^2/2 & 0 & 0 & 0 \\ 0 & T & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{4}$$

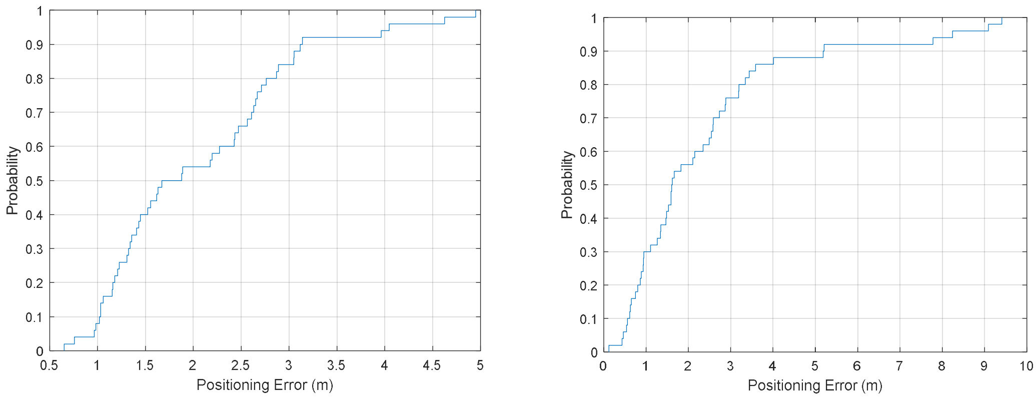
$$\boldsymbol{h}\left(\boldsymbol{x}_k\right) = \left[h_1\left(\boldsymbol{x}_k\right) \quad h_2\left(\boldsymbol{x}_k\right) \quad h_3\left(\boldsymbol{x}_k\right) \quad g_0\left(\boldsymbol{x}_k\right) \quad g_1\left(\boldsymbol{x}_k\right) \quad g_2\left(\boldsymbol{x}_k\right) \quad g_3\left(\boldsymbol{x}_k\right)\right]^T \tag{5}$$

$$h_i\left(\boldsymbol{x}_k\right) = \sqrt{\left(x_k - x_{TRPi}\right)^2 + \left(y_k - y_{TRPi}\right)^2 + 4} - \sqrt{\left(x_k - x_{TRP0}\right)^2 + \left(y_k - y_{TRP0}\right)^2 + 4} + b_{i,k} \tag{6}$$

$$g_i\left(\boldsymbol{x}_k\right) = A_i - 10\eta_i \log\left(\sqrt{\left(x_k - x_{TRPi}\right)^2 + \left(y_k - y_{TRPi}\right)^2 + 4}\right) \tag{7}$$

where $\boldsymbol{x}_k = \left[x_k \quad v_{x,k} \quad y_k \quad v_{y,k} \quad b_{1,k} \quad b_{2,k} \quad b_{3,k}\right]^T$, x_k and y_k are the horizontal coordinates of the terminal at time k, $v_{x,k}$ and $v_{y,k}$ are the horizontal velocities of the terminal at time k, $b_{1,k}$, $b_{2,k}$ and $b_{3,k}$ are the TAEs of the TRPs at time k, $\boldsymbol{w}_{k-1}$ is the process noise at time k-1, T is the sampling interval, $\boldsymbol{z}_k = \begin{bmatrix} \gamma_{1,k} & \gamma_{2,k} & \gamma_{3,k} & \rho_{0,k} & \rho_{1,k} & \rho_{2,k} & \rho_{3,k} \end{bmatrix}^T$, $\gamma_{i,k}$ is the TDOA measurement of TRPi and TRP0, $\rho_{i,k}$ is the RSRP measurement of TRPi, x_{TRPi} and y_{TRPi} are the horizontal coordinates of the TRPi, A_i and η_i are the model parameters of the TRPi, $\boldsymbol{v}_k$ is the measurement noise at time k. Based on the state space model proposed above, the EKF can be utilized to estimate the location of the terminal, recursively.

Considering the outliers caused by the weak LOS paths and NLOS paths, the measurement noise $\boldsymbol{v}_k$ is modeled as a heavy-tailed non-Gaussian noise. Therefore, to deal with the outliers in the measurements, a maximum correntropy criterion (MCC)-based EKF is developed. The MCC-based EKF can handle the heavy-tailed non-Gaussian noise by using a robust cost function. The localization results of the proposed algorithm are shown in Fig3. As shown in Fig3, the positioning error at 75% CDF is about 3m.



(a) Testing_Trial_A (b) Testing_Trial_B

Fig.3 ECDF of the positioning error