APPENDIX

Target Localization Using Quantized Observations in Delay-Sensitive Networks

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I. APPENDIX

Here, we derive the squared position error bound (SPEB) of \mathbf{p}^+ in Proposition 1. The unknown parameters are collected as $\mathbf{\theta} = [(\mathbf{p}^+)^T, \mathbf{p}^T]^T$ and the log-likelihood function is

$$\ln f(\boldsymbol{z}, \boldsymbol{\theta}) = \ln f(\boldsymbol{z}|\boldsymbol{p}) + \ln f(\boldsymbol{p}^{+}|\boldsymbol{p}) + \ln f(\boldsymbol{p}), \quad (1)$$

where f(x) denotes the probability density function (PDF) $f_{\mathbf{x}}(x)$ of the random vector \mathbf{x} unless specified otherwise. Then, the Fisher information matrix (FIM) of $\mathbf{0}$ can be decomposed into three parts, as follows [1]:

$$J_{\theta}(b) = J_{\text{ob}}(b) + J_{\text{M}}(b) + J_{\text{P}}$$
 (2)

where $J_{ob}(b)$, $J_{M}(b)$, and J_{P} represent FIMs from quantized observations, target motions, and a prior knowledge of the target, respectively. The expression of $J_{ob}(b)$ is

$$\boldsymbol{J}_{ob}(\boldsymbol{b}) = -\mathbb{E}_{\boldsymbol{z}, \boldsymbol{p}} \{ \Delta_{\boldsymbol{\theta}}^{\boldsymbol{\theta}} \ln f(\boldsymbol{z}|\boldsymbol{p}) \}$$
 (3)

where $\Delta_{\theta}^{\theta} \ln f(z|p)$ denotes $\partial^2 \ln f(z|p)/\partial \theta \partial \theta^{\mathrm{T}}$ and (3) is rewritten since the observation is not associated with \mathbf{p}^+ as

$$\boldsymbol{J}_{ob}(\boldsymbol{b}) = \begin{bmatrix} \boldsymbol{O} & \boldsymbol{O} \\ \boldsymbol{O} & \mathbb{E}_{\mathbf{p}} \left\{ \boldsymbol{J}_{\mathbf{Q}}(\boldsymbol{b}) \right\} \end{bmatrix}$$
(4)

where O denotes the 2×2 zero matrix and

$$\boldsymbol{J}_{\mathbf{Q}}(\boldsymbol{b}) = -\mathbb{E}_{\mathbf{z}|\mathbf{p}} \{ \Delta_{\boldsymbol{p}}^{\boldsymbol{p}} \ln f(\boldsymbol{z}|\boldsymbol{p}) \}. \tag{5}$$

The expression for $J_Q(b)$ is computed similarly to previous studies analyzing performance limits for unknown parameters from quantized observations [2]. It is provided as follows:

$$\boldsymbol{J}_{Q}(\boldsymbol{b}) = \sum_{n=1}^{N_{a}} \sum_{k=1}^{K} \gamma_{n} \rho_{n,k}(b_{n}) \frac{\partial s_{k}(\tau_{n})}{\partial \boldsymbol{p}} \frac{\partial s_{k}(\tau_{n})}{\partial \boldsymbol{p}^{T}}, \quad (6)$$

where $\gamma_n = |\beta_n|^2/\sigma_n^2$ represents the signal-to-noise ratio (SNR) at n-th agent, $s_k(\tau_n)$ refers to the k-th element of the signal vector $s(f_s;\tau_n)$, and $\rho_{n,k}(b_n)$ represents the quantized coefficient at k-th quantizer of n-th agent, calculated by

$$\rho_{n,k}(b_n) = \frac{1}{2\pi} \sum_{l=1}^{L_n} \frac{\left(e^{-r_{l+1}^2/2} - e^{-r_l^2/2}\right)^2}{\Phi(r_{l+1}) - \Phi(r_l)},\tag{7}$$

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$$r_l = [u_l - \beta_n s_k(\tau_n)] / \sigma_n, \quad l = 1, 2, \dots, L_n - 1$$
 (8)

where $\Phi(x)$ denotes the tail distribution function of the standard norm distribution with $\Phi(x)=\frac{1}{\sqrt{2\pi}}\int_{-\infty}^x e^{-\frac{t^2}{2}}\ dt$ [3]. Subsequently, the matrix ${\pmb J}_{\rm M}({\pmb b})$ can be computed as follows:

$$J_{\mathrm{M}}(\boldsymbol{b}) = -\mathbb{E}_{\mathbf{p},\mathbf{p}^{+}} \left\{ \Delta_{\boldsymbol{\theta}}^{\boldsymbol{\theta}} \ln f(\boldsymbol{p}^{+}|\boldsymbol{p}) \right\}, \tag{9}$$

which can be calculated as

$$\boldsymbol{J}_{\mathrm{M}}(\boldsymbol{b}) = \frac{1}{\alpha \Delta t(\boldsymbol{b})} \begin{bmatrix} \boldsymbol{I}_{2} & -\boldsymbol{I}_{2} \\ -\boldsymbol{I}_{2} & \boldsymbol{I}_{2} \end{bmatrix}. \tag{10}$$

Furthermore, the FIM from the a priori knowledge of the target is independent of the bit-depth, which is given by

$$\boldsymbol{J}_{P} = -\mathbb{E}_{\mathbf{p}} \{ \Delta_{\boldsymbol{p}}^{\boldsymbol{p}} \ln f(\boldsymbol{p}) \}. \tag{11}$$

Due to the a priori knowledge only relies on **p**, we can obtain

$$J_{P} = \begin{bmatrix} O & O \\ O & \sigma_{0}^{-2} I_{2} \end{bmatrix}$$
 (12)

Substituting (4), (10), and (12) into (2), we can obtain the partition of the FIM $J_{\theta}(b)$ is given by

$$J_{\theta}(b) = \begin{bmatrix} A & -A \\ -A^{\mathsf{T}} & A + W \end{bmatrix}$$
 (13)

where $\mathbf{A} = 1/[\alpha \Delta t(\mathbf{b})] \mathbf{I}_2$ and $\mathbf{W} = \mathbb{E} \{ \mathbf{J}_{Q}(\mathbf{b}) \} + \sigma_0^{-2} \mathbf{I}_2$. Then, the equivalent Fisher information matrix (EFIM) for estimating \mathbf{p}^+ is given by [4]

$$J_{++}^{e}(b) = A - A(A + W)^{-1}A^{T}.$$
 (14)

According to the matrix inverse lemma, we can obtain the closed-from EFIM for estimating \mathbf{p}^+ , which is given by

$$\boldsymbol{J}_{+,+}^{e}(\boldsymbol{b}) = \left[\boldsymbol{W}^{-1} + \alpha \Delta t(\boldsymbol{b}) \boldsymbol{I}_{2}\right]^{-1}$$
 (15)

Finally, the closed-form SPEB for estimating \mathbf{p}^+ is given as

$$\mathcal{P}(\mathbf{p}^+; \boldsymbol{b}) = \operatorname{tr} \left\{ \left(\mathbb{E}_{\mathbf{p}} \{ \boldsymbol{J}_{\mathbf{Q}}(\boldsymbol{b}) \} + \sigma_0^{-2} \boldsymbol{I}_2 \right)^{-1} \right\} + 2\alpha \Delta t(\boldsymbol{b}), (16)$$

which completes the proof of Proposition 1.

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