

Supplementary Material

Proof of Lemma 2. We subtract (1) from (4) to get

$$\begin{aligned}\hat{x}_{i,t+1} - x_{t+1} &= a \left(\sum_{j \in \mathcal{N}_i} p_{ij} \hat{x}_{j,t} - x_t + \alpha(y_{i,t} - \hat{x}_{i,t}) \right) - r_t \\ &= a \left(\sum_{j \in \mathcal{N}_i} p_{ij} (\hat{x}_{j,t} - x_t) + \alpha(y_{i,t} - \hat{x}_{i,t}) \right) - r_t,\end{aligned}$$

where we used Assumption 1 in the latter step. Replacing $y_{i,t}$ from (2) in above, and simplifying using definition of $\hat{\xi}_{i,t}$, yields

$$\begin{aligned}\hat{\xi}_{i,t+1} &= a \left(\sum_{j \in \mathcal{N}_i} p_{ij} \hat{\xi}_{j,t} + \alpha(y_{i,t} - \hat{x}_{i,t}) \right) - r_t \\ &= a \left(\sum_{j \in \mathcal{N}_i} p_{ij} \hat{\xi}_{j,t} - \alpha \hat{\xi}_{i,t} \right) + (a\alpha)w_{i,t} - r_t.\end{aligned}$$

Using definition (6) to write the above in the matrix form completes the proof for $\hat{\xi}_t$. The proof for $\tilde{\xi}_t$ follows precisely in the same fashion. \square

Proof of Proposition 3. We start by the fact that the innovation and observation noise are zero mean, so (7) implies $\mathbb{E}[\hat{\xi}_{t+1}] = Q\mathbb{E}[\hat{\xi}_t]$, and $\mathbb{E}[\tilde{\xi}_{t+1}] = Q\mathbb{E}[\tilde{\xi}_t]$. Therefore, for mean stability of the linear equations, the spectral radius of Q must be less than unity. Considering the expression for Q from (8), for a fixed α we must have

$$|a| < \frac{1}{\rho(P - \alpha I_N)} = \frac{1}{\max\{1 - \alpha, |\alpha - \lambda_N(P)|\}}. \quad (26)$$

To maximize the right hand side over α , we need to solve the min-max problem

$$\min_{\alpha} \left\{ \max\{1 - \alpha, |\alpha - \lambda_N(P)|\} \right\}.$$

Noting that $1 - \alpha$ and $\alpha - \lambda_N(P)$ are straight lines with negative and positive slopes, respectively, the minimum occurs at the intersection of the two lines. Evaluating the right hand side of (26) at the intersection point $\alpha^* = \frac{1 + \lambda_N(P)}{2}$, completes the proof. \square

Proof of Theorem 5. We present the proof for $\tilde{\text{MSD}}(P, \alpha)$ by observing that (7)

$$\mathbb{E}[\tilde{\xi}_{t+1} \tilde{\xi}_{t+1}^T] = Q\mathbb{E}[\tilde{\xi}_t \tilde{\xi}_t^T]Q^T + \mathbb{E}[\tilde{s}_t \tilde{s}_t^T],$$

since the innovation and observation noise are zero mean and uncorrelated. Therefore, letting $\tilde{S} = \mathbb{E}[\tilde{s}_t \tilde{s}_t^T]$, since $\rho(Q) < 1$ by hypothesis, the steady state satisfies a Lyapunov equation as below

$$\tilde{\Sigma} = Q\tilde{\Sigma}Q^T + \tilde{S}.$$

Let $Q = Q^T = U\Lambda U^T$ represent the Eigen decomposition of Q . Let also u_i denote the i -th eigenvector of Q corresponding to eigenvalue λ_i . Under stability of Q the solution of the Lyapunov equation is as follows

$$\begin{aligned}\tilde{\Sigma} &= \sum_{\tau=0}^{\infty} Q^{\tau} \tilde{S} Q^{\tau} \\ &= \sum_{\tau=0}^{\infty} \sum_{i=1}^N \sum_{j=1}^N \lambda_i^{\tau} u_i u_i^T \tilde{S} \lambda_j^{\tau} u_j u_j^T \\ &= \sum_{i=1}^N \sum_{j=1}^N u_i u_i^T \tilde{S} u_j u_j^T \sum_{\tau=0}^{\infty} \lambda_i^{\tau} \lambda_j^{\tau} \\ &= \sum_{i=1}^N \sum_{j=1}^N \frac{u_i u_i^T \tilde{S} u_j u_j^T}{1 - \lambda_i \lambda_j}.\end{aligned}$$

Therefore, the $\tilde{\text{MSD}}$ defined in 4, can be computed as

$$\tilde{\text{MSD}} = \frac{1}{N} \text{Tr} \left(\sum_{i=1}^N \sum_{j=1}^N \frac{u_i u_i^\top \tilde{S} u_j u_j^\top}{1 - \lambda_i \lambda_j} \right) = \frac{1}{N} \sum_{i=1}^N \sum_{j=1}^N \frac{(u_j^\top u_i)(u_i^\top \tilde{S} u_j)}{1 - \lambda_i \lambda_j} = \frac{1}{N} \sum_{i=1}^N \frac{u_i^\top \tilde{S} u_i}{1 - \lambda_i^2},$$

where we used the fact that $u_j^\top u_i = 0$, for $i \neq j$, and $u_i^\top u_i = 1$, for any $i \in \mathcal{V}$. Taking into account that $Q = a(P - \alpha I_N)$ and $\tilde{S} = \sigma_r^2(\mathbf{1}_N \mathbf{1}_N^\top) + (a^2 \alpha^2 \sigma_w^2) P^2$, we derive

$$\begin{aligned} \tilde{\text{MSD}} &= \frac{1}{N} \sum_{i=1}^N \frac{u_i^\top (\sigma_r^2(\mathbf{1}_N \mathbf{1}_N^\top) + (a^2 \alpha^2 \sigma_w^2) P^2) u_i}{1 - \lambda_i^2} \\ &= \frac{1}{N} \sum_{i=1}^N \frac{(u_i^\top \mathbf{1}_N)^2 \sigma_r^2}{1 - \lambda_i^2} + \frac{1}{N} \sum_{i=1}^N \frac{a^2 \alpha^2 \sigma_w^2 \lambda_i^2(P)}{1 - \lambda_i^2} \\ &= \frac{\sigma_r^2}{1 - a^2(1 - \alpha)^2} + \frac{1}{N} \sum_{i=1}^N \frac{a^2 \alpha^2 \sigma_w^2 \lambda_i^2(P)}{1 - a^2(\lambda_i(P) - \alpha)^2}, \end{aligned}$$

where the last step is due to the facts that $\lambda_i = a(\lambda_i(P) - \alpha)$ and $\mathbf{1}_N / \sqrt{N}$ is one of the eigenvectors of Q with corresponding eigenvalue $a(1 - \alpha)$, so it is orthogonal to other eigenvectors, i.e., $u_i^\top \mathbf{1}_N = 0$, for $u_i \neq \mathbf{1}_N / \sqrt{N}$. The proof for $\tilde{\text{MSD}}$ follows in the same fashion. \square

Proof of Theorem 8. The closed form solution of the error process (7) is,

$$\xi_{t+1} = Q^{t+1} \xi_0 + \sum_{\tau=0}^t Q^{t-\tau} s_\tau,$$

which implies

$$\begin{aligned} \xi_{t+1} \xi_{t+1}^\top &= Q^{t+1} \xi_0 \xi_0^\top Q^{t+1} + Q^{t+1} \xi_0 \left(\sum_{\tau=0}^t Q^{t-\tau} s_\tau \right)^\top + \left(\sum_{\tau=0}^t Q^{t-\tau} s_\tau \right) \xi_0^\top Q^{t+1} \\ &\quad + \left(\sum_{\tau=0}^t Q^{t-\tau} s_\tau \right) \left(\sum_{\tau=0}^t Q^{t-\tau} s_\tau \right)^\top, \end{aligned} \quad (27)$$

since Q is symmetric. One can see that

$$\left\| \frac{1}{T} \sum_{t=1}^T Q^t \xi_0 \xi_0^\top Q^t \right\| \leq \frac{1}{T} \left(\frac{\|\xi_0\|^2}{1 - \rho^2(Q)} \right),$$

and

$$\left\| \frac{1}{T} \sum_{t=0}^{T-1} Q^{t+1} \xi_0 \left(\sum_{\tau=0}^t Q^{t-\tau} s_\tau \right)^\top \right\| \leq \frac{\|\xi_0\| s}{T} \sum_{t=0}^{T-1} \rho(Q)^{t+1} \sum_{\tau=0}^t \rho(Q)^{t-\tau} \leq \frac{1}{T} \left(\frac{s \|\xi_0\|}{(1 - \rho(Q))^2} \right).$$

On the other hand, as we see in the proof of Theorem 5, letting $S = \mathbb{E}[s_\tau s_\tau^\top]$, we have $\Sigma = \sum_{\tau=0}^\infty Q^\tau S Q^\tau$. Based on definition (18), equation (27), and the bounds above, we derive

$$\begin{aligned} R(T) &\leq \frac{1}{T} \left(\frac{\|\xi_0\|^2}{1 - \rho^2(Q)} \right) + \frac{1}{T} \left(\frac{2s \|\xi_0\|}{(1 - \rho(Q))^2} \right) \\ &\quad + \frac{1}{T} \left\| \sum_{t=0}^{T-1} \left(\sum_{\tau=0}^t Q^{t-\tau} s_\tau \right) \left(\sum_{\tau=0}^t Q^{t-\tau} s_\tau \right)^\top - \sum_{\tau=0}^t Q^\tau S Q^\tau \right\| + \left\| \frac{1}{T} \sum_{t=0}^{T-1} \sum_{\tau=t+1}^\infty Q^\tau S Q^\tau \right\|. \end{aligned} \quad (28)$$

Let

$$H(s_0, \dots, s_{T-1}) = \sum_{t=0}^{T-1} \left(\sum_{\tau=0}^t Q^{t-\tau} s_\tau \right) \left(\sum_{\tau=0}^t Q^{t-\tau} s_\tau \right)^\top,$$

and observe that $\mathbb{E}[H(s_0, \dots, s_{T-1})] = \sum_{t=0}^{T-1} \sum_{\tau=0}^t Q^\tau S Q^\tau$. It can be verified that for any $0 \leq t < T$,

$$\|H(s_0, \dots, s_t, \dots, s_{T-1}) - H(s_0, \dots, s'_t, \dots, s_{T-1})\| \leq \frac{4s^2}{(1 - \rho(Q))^2}.$$

Thus, letting $Var = \frac{16Ts^4}{(1 - \rho(Q))^4}$, and appealing to Lemma 7, we get

$$\mathbb{P}\left\{\left\|\sum_{t=0}^{T-1} \left(\sum_{\tau=0}^t Q^{t-\tau} s_\tau\right) \left(\sum_{\tau=0}^t Q^{t-\tau} s_\tau\right)^\top - \sum_{\tau=0}^t Q^\tau S Q^\tau\right\| \geq c\right\} \leq Ne^{-c^2/8Var}.$$

Setting the probability above equal to δ , this implies that with probability at least $1 - \delta$, we have

$$\frac{1}{T} \left\|\sum_{t=0}^{T-1} \left(\sum_{\tau=0}^t Q^{t-\tau} s_\tau\right) \left(\sum_{\tau=0}^t Q^{t-\tau} s_\tau\right)^\top - \sum_{\tau=0}^t Q^\tau S Q^\tau\right\| \leq \frac{1}{\sqrt{T}} \frac{8s^2 \sqrt{2 \log \frac{N}{\delta}}}{(1 - \rho(Q))^2}.$$

Moreover, we evidently have

$$\left\|\frac{1}{T} \sum_{t=0}^{T-1} \sum_{\tau=t+1}^{\infty} Q^\tau S Q^\tau\right\| \leq \frac{1}{T} \left(\frac{s^2}{(1 - \rho^2(Q))^2}\right).$$

Plugging the two bounds above in (28) completes the proof. \square

Proof of Proposition 9. Considering the expression for MSD in Theorem 5, we have

$$\begin{aligned} \tilde{\text{MSD}}(P, \alpha) - \tilde{\text{MSD}}(P_{-\epsilon}, \alpha) &= \tilde{W}_{MSD}(P, \alpha) - \tilde{W}_{MSD}(P_{-\epsilon}, \alpha) \\ &\propto \sum_{i=1}^N \frac{(\lambda_i(P) - \lambda_i(P_{-\epsilon}))((1 - \alpha^2 a^2)(\lambda_i(P_{-\epsilon}) + \lambda_i(P)) + 2a^2 \alpha \lambda_i(P) \lambda_i(P_{-\epsilon}))}{(1 - a^2(\lambda_i(P) - \alpha)^2)(1 - a^2(\lambda_i(P_{-\epsilon}) - \alpha)^2)}. \end{aligned}$$

Based on definitions (20) and (21), it follows from Weyl's eigenvalue inequality that $\lambda_k(P) - \lambda_k(P_{-\epsilon}) \leq \lambda_1(\epsilon \Delta P(i, j)) = 0$, for any $k \in \mathcal{V}$. Combined with the assumptions $P \geq 0$ and $|a\alpha| < 1$, this implies that the numerator of the expression above is always non-positive. The denominator is always positive due to stability of the error process $\tilde{\xi}_t$ in (7), and hence, $\tilde{\text{MSD}}(P, \alpha) \leq \tilde{\text{MSD}}(P_{-\epsilon}, \alpha)$. \square