Output feedback stochastic MPC with packet losses

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Abstract: The paper considers constrained linear systems with stochastic additive disturbances and noisy measurements transmitted over a lossy communication channel. We propose a model predictive control (MPC) law that minimizes a discounted cost subject to a discounted expectation constraint. Sensor data is assumed to be lost with known probability, and data losses are accounted for by expressing the predicted control policy as an affine function of future observations, which results in a convex optimal control problem. An online constraint-tightening technique ensures recursive feasibility of the online optimization and satisfaction of the expectation constraint without bounds on the distributions of the noise and disturbance inputs. The cost evaluated along trajectories of the closed loop system is shown to be bounded by the optimal predicted cost. A numerical example is given to illustrate these results.

Keywords: Model predictive control, output feedback, packet drops, chance constraints, convex optimization.

1. INTRODUCTION

Robust model predictive control often considers worst-case disturbance bounds, so that hard constraints on system states and control inputs are satisfied for all possible disturbances (Mayne et al., 2000; Mesbah, 2016; Kouvaritakis and Cannon, 2015). However, worst-case disturbance bounds can be extremely conservative or even non-existent, which motivates the development of stochastic MPC with chance constraints. In many applications of practical interest, system states cannot be measured directly and instead have to be estimated from output measurements. Existing stochastic MPC algorithms incorporating state estimation (e.g. Cannon et al., 2012; Dai et al., 2015) typically do not consider optimizing state feedback gains online, and the estimator gain is typically chosen as the steady state Kalman filter gain.

Control systems that rely on sensor signals transmitted over a network must tolerate communication delays and data losses. These pose additional challenges for estimation and control problems when constraints are present. From a control perspective, these features can be modelled as information losses by random processes, such as Bernoulli processes (Sinopoli et al., 2004) or Markov chains (Leong et al., 2017). In Sinopoli et al. (2004), the arrival of output observations is modelled as a Bernoulli process and fundamental results are derived, including bounds on the critical value for the arrival probability of the observation update and convergence properties of the algebraic Riccati equation for Kalman filters with intermittent observations. In Schenato et al. (2007), it is shown that the well-known separation principle holds with sensor packet losses, whereas this is not the case if constraints are present. Mishra et al. (2019) consider the problem of controlling linear systems with unbounded additive disturbances and measurement noise by using an affine policy, where both sensor measurements and control actions are lost with given probabilities. Alternatively, these problems can be modelled as jump linear systems (Mariton, 1990) switching between different states according to a transition probability matrix.

This paper designs an output-feedback MPC algorithm to minimize a discounted cost function subject to a discounted expectation constraint, assuming sensor measurements to be lost with a given probability. The discount setting is common to many control problems (e.g. Bertsekas, 1995; Van Parys et al., 2013; Kouvaritakis et al., 2003; Kamgarpour and Summers, 2017), and an appropriate discounting factor can provide stability guarantees (Postoyan et al., 2017). In this work, the discount factor allows consideration of unbounded disturbances and measurement noise, and we derive bounds on the cost and constraints for the closed loop system using a constraint-tightening technique (Yan et al., 2018). Instead of choosing the future control policy as pre-stabilising feedback with perturbations (Cannon et al., 2011), we parameterise predicted control inputs as affine functions of future output measurements and show that the problem of optimizing the associated feedback gains is convex. This allows the distributions of future states to be controlled even when output measurements are lost.

This paper is organised as follows. We describe the control problem in Section 2, and introduce the controller parametrization and implementation in Section 3. We compute predicted state and control sequences via their first and second moments in Section 4. In Section 5, we derive the terminal conditions and give explicit expressions for the cost and constraints. Our main results, including a closed loop cost bound and constraint satisfaction, are in Section 6. Section 7 provides a numerical example and the paper is concluded in Section 8.
Notation: The $n \times n$ identity matrix is $I_{n \times n}$, and the $n \times m$ matrix with all elements equal to 1 is $1_{n \times m}$. The vectorized form of a matrix $A = [a_1 \ldots a_n]$ is $\text{vec}(A) := [a_1^T \ldots a_n^T]^T$ and $A \otimes B$ is the Kronecker product. The Euclidean norm is $\|x\|$ and, for a matrix $Q$, $Q \succ 0$ ($Q \succeq 0$) indicates that $Q$ is positive definite (semidefinite) and $\|x\|_Q^2 := x^T Q x$.

2. PROBLEM DESCRIPTION

2.1 System model and feedback information

We assume a system with linear discrete time dynamics

$$x_{k+1} = Ax_k + Bu_k + Dw_k,$$  \hspace{0.5cm} (1a)

$$y_k = Cx_k + v_k,$$  \hspace{0.5cm} (1b)

where $x \in \mathbb{R}^n$, $u \in \mathbb{R}^m$, $y \in \mathbb{R}^n$, $z \in \mathbb{R}^n$ are the state, control input, sensor measurement, and the measurement information received by the controller respectively. The disturbance, measurement noise and packet loss sequences, $\{w_k\}_{k=0}^\infty$, $\{v_k\}_{k=0}^\infty$ and $\{\gamma_k\}_{k=0}^\infty$, are assumed to have independent, identically distributed (i.i.d.) elements with $\mathbb{E}\{w_k\} = 0$, $\mathbb{E}\{v_k v_k^T\} = \Sigma_v \succeq 0$, $\mathbb{E}\{v_k\} = 0$, $\mathbb{E}\{v_k v_k^T\} = \Sigma_v \succeq 0$, $\mathbb{P}\{\gamma_k = 0\} = 1 - \lambda$, $\mathbb{P}\{\gamma_k = 1\} = \lambda$.

The variable $\gamma_k \in \{0, 1\}$ indicates whether sensor data arrives at the $k$th sampling instant is received by the controller. The information available to the controller at time $k$ consists of $\{u_i\}_{i=1}^{k-1}$, $\{(x_i, \gamma_i)\}_{i=0}^{k-1}$, the initial mean $\mathbb{E}\{x_0\} = \hat{x}_0$, and covariance $\mathbb{E}\{(x_0 - \hat{x}_0)(x_0 - \hat{x}_0)^T\} = \Sigma_0$ of the model state.

We define the information sets

$$I_k := \{I_{k-1}, (x_k, \gamma_k)\},$$  \hspace{0.5cm} $\mathcal{U}_k := \{\mathcal{U}_{k-1}, u_k\},$

for all $k \geq 0$, where $I_{-1} := \{\emptyset, \Sigma_0\}$, $\mathcal{U}_{-1} := \{\}$. Finally, we define conditional expectation operators as

$$\mathbb{E}_k \{\cdot\} := \mathbb{E}\{\cdot | \mathcal{U}_{k-1}, I_{k-1}\},$$  \hspace{0.5cm} $\mathbb{E}\{\cdot\} := \mathbb{E}_0 \{\cdot\}.$

Assumption 1. The pair $(A, B)$ is stabilizable, and $(A, C)$ is detectable.

2.2 Optimal control problem

We will employ a finite-horizon control policy with input at time $k$ in the form

$$u_{ik} = \kappa_i(\theta_k, \mathcal{U}_{k-1}, I_{k+1})$$

where $u_{ik}$ for $i = 0, 1, \ldots$ is the prediction of $u_{k+i}$ at time $k$, and $\theta_k$ is a vector of controller parameters at time $k$. The dependence of $\kappa_i(\cdot)$ on the sets $\mathcal{U}_{k-1}$ and $I_{k+1}$ ensures causality and the dependence on $\theta_k$ is chosen so that the optimal parameter vector, denoted $\theta_k^*$, will be the solution of a convex problem.

Assumption 2. (i). The probability, $\lambda$, of successfully receiving sensor measurements is known. (ii). When $\theta_k^*$ is computed, $(x_{k+i}, \gamma_{k+i})$ are unknown for all $i \geq 0$.

Assumption 2 requires $\theta_k^*$ to be a function of $\mathcal{U}_{k-1}$ and $I_{k-1}$, and we therefore assume that $\theta_k^*$ is computed online prior to the $\lambda$th sampling instant. However $(x_k, \gamma_k)$ is known when the control law

$$u_k = \kappa_0(\theta_k^*, \mathcal{U}_{k-1}, I_k)$$

is applied to the plant.

We consider the problem of minimizing the discounted sum of expected future values of $\|x_k\|_Q^2 + \|u_k\|_R^2$, where $Q \succeq 0$ and $R \succ 0$. This minimization is subject to a constraint on the discounted sum of second moments of an auxiliary output, defined for given matrix $H$ by $\xi_k = H x_k$, so that

$$\theta_k^* = \arg\min_{\theta_k} \sum_{i=0}^\infty \beta^i \mathbb{E}_k \{\|x_{i+k}\|_Q^2 + \|u_{i+k}\|_R^2\}$$

$$\text{s.t.} \sum_{i=0}^\infty \beta^i \mathbb{E}_k \{\|H x_{i+k}\|^2\} \leq \epsilon. \hspace{0.5cm} (2)$$

Here $\beta \in (0, 1)$ is a discounting factor and $\epsilon$ is a given bound on this infinite discounted sum of second moments. Instead of solving (2) directly, the control problem to be solved at time $k$ is given by

$$\theta_k^* = \arg\min_{\theta_k} \sum_{i=0}^\infty \beta^i \mathbb{E}_k \{\|x_{i+k}\|_Q^2 + \|u_{i+k}\|_R^2\}$$

$$\text{s.t.} \sum_{i=0}^\infty \beta^i \mathbb{E}_k \{\|H x_{i+k}\|^2\} \leq \mu k. \hspace{0.5cm} (3)$$

Here $\mu_0 = \epsilon$ and, for all $k > 0$, $\mu_k$ is chosen as described in Section 6 to ensure that (3) is recursively feasible and that the constraint in (2) is satisfied with $k = 0$ by the closed loop system.

3. CONTROLLER PARAMETERIZATION

Consider the output feedback control law defined by an observer and an affine feedback law:

$$\hat{x}_k = A \hat{x}_{k-1} + Bu_{k-1} + \hat{x}_k = \hat{x}_k + \gamma_k M (y_k - C \hat{x}_k),$$ \hspace{0.5cm} (4a)

$$u_k = K \hat{x}_k + c_k. \hspace{0.5cm} (4b)$$

with $\hat{x}_0 = \mathbb{E}\{x_0\}$, where $\hat{x}_k$ and $\hat{x}_k$ are the a priori estimate and the posteriori estimate of $x_k$, respectively. A simplistic parameterization of the predicted control law $\kappa_i(\cdot)$ could be obtained if the observer gain $M$ and feedback gain $K$ were fixed and the optimization variables in problem (3) were defined as $\theta_k = \{c_0, \ldots, c_{N-1}\}$ for some fixed $N$, with the predicted control sequence defined as $u_{ik} = K \hat{x}_{i+k} + c_{i+k}$. Although this would require a number of optimization variables that grows only linearly with $N$, the parameters $\{c_0, \ldots, c_{N-1}\}$ constitute an open loop control sequence that does not vary with the future measurement noise and disturbance realizations. This is likely to provide poor performance and small sets of feasible initial conditions when the probability of packet loss is non-zero.

By using a parameterization that allows the dependence of the predicted control sequence on future realizations of model uncertainty to be optimized, the predicted probability distributions of states and control inputs can be controlled explicitly. This provides flexibility to balance conflicting requirements for performance and constraint satisfaction. However, similarly to the case of predicted control laws in which state feedback gains are decision variables (Löfberg, 2003; Goulart et al., 2006), the cost and constraints of problem (3) are nonconvex if time-varying gains $M, K$ are considered as optimization variables. On the other hand, if predicted control inputs are parameterized in terms of affine functions of the future output measurements received by the controller, then the dependence of the first and second moments of predicted states and inputs on controller parameters is convex. Moreover, by incorporating affine terms in the future innovation sequence, a predicted control law with arbitrary linear dependence of
κ_i(·) on the received sensor measurements can be obtained. This approach allows the future control sequence to be optimized at every sampling instant, including those at which information from sensors is lost.

We therefore express the i steps ahead predicted control input u_{i,k}, for all i = 0, 1, ..., as
\[ u_{i,k} = K\hat{x}_{i,k} + c_{i,k} + d_{i,k}, \] (5a)

\[ d_{i,k} = \gamma_i L_{i,0|0}(y_{i0} - C\hat{x}_{i,k}) + \gamma_i L_{i,1|1}(y_{i1} - C\hat{x}_{i,k}) + \cdots + \gamma_i L_{i,i|k}(y_{i,k} - C\hat{x}_{i,k}), \] (5b)

\[ \hat{x}_{i+1|k} = A\hat{x}_{i,k} + Bu_{i,k} + \gamma_i AM(y_{i,k} - C\hat{x}_{i,k}), \] (5c)

where \( c_i \) and \( y_{i,k} \) are random variables, denoting the i-step-ahead predicted packet loss and sensor measurement at time \( k \), respectively. Then, for all \( i = 0, 1, \ldots \) the predicted state estimate satisfies
\[ \hat{x}_{i+1|k} = \Psi \hat{x}_{i,k} + B(c_{i,k} + d_{i,k}) + \gamma_i AM(y_{i,k} - C\hat{x}_{i,k}) \] (6)

where \( \Psi := A + BK \). Since \( \hat{x}_{i+1|k} = A\hat{x}_{i,k} + Bu_{i,k} + Dw_{i,k} \) the predicted estimation error evolves according to
\[ \hat{x}_{i+1|k} - \hat{x}_{i|k} = \Psi \hat{x}_{i,k} - \hat{x}_{i,k} + \gamma_i AM(y_{i,k} - C\hat{x}_{i,k}) \] (7)
with \( \Psi := A(I - \gamma_i MC) \). These relationships allow the first and second moments of \( x_{i,k} \) to be determined in terms of the decision variable \( \theta_k \), which consists of the parameters \{\( \{c_{0|k}, \ldots , c_{N-1|k}\} \) and feedback gains \( L_{0,0|k}, L_{1,0|k}, L_{1,1|k}, \ldots , L_{N-1,0|k}, L_{N-1,1|k} \) \}.

The gains \( K \) and \( M \) in the predicted control law (5a-c) are chosen offline and satisfy the following assumption.

Assumption 3. \( \xi_{i+1} = (A + BK)\xi_i \) is asymptotically stable and \( \xi_{i+1} = A(I - \gamma_i MC)\xi_i \) is mean-square stable (Kushner, 1971).

Remark 1. Gains \( K \) and \( M \) exist satisfying Assumption 3 if Assumption 1 holds and if the probability, \( \lambda \), of successfully receiving a sensor measurement is greater than some critical value (e.g. Sinopoli et al., 2004). Suitable choices for \( K \) and \( M \) are the optimal gains for (3) in the absence of constraints, or the certainty equivalent LQ feedback gain for a problem with state and control weighting matrices \( Q \) and \( R \) and the steady state Kalman filter gain (Sinopoli et al., 2004). We note also that time-varying gains \( K_k \) and \( M_k \) exist when \( \gamma_k \) is known in advance.

3.1 Controller implementation

The control law is implemented by the following procedure.

(i). Given \( u_{k-1} \) and \( L_{k-1} \), solve problem (3) for \( \theta^*_k \).

(ii). Given \( x_k \) and \( \hat{x}_k = \gamma_k y_k \):

(a). apply the control input \( u_k = K\hat{x}_k + c_{0|k} + \gamma_k L_{0,0|k}(y_{0} - C\hat{x}_k) \),

(b). update the state estimate \( \hat{x}_{k+1} = A\hat{x}_k + Bu_k + \gamma_k AM(y_{k} - C\hat{x}_k) \).

Note that this receding horizon control law includes (4) as a special case, since \( u_k \) and \( \hat{x}_{k+1} \) in step (ii) would be equal to their counterparts in (4) if \( (c_{0|k}, L_{0,0|k}) = (c_k, KM) \).

4. PREDICTED STATE AND CONTROL SEQUENCES

To simplify notation we express the predicted control law in terms of vectorized sequences, with \( \mathbf{x}_k \) denot-

\[ \begin{bmatrix} I \\ \Psi_{0|k} \\ \vdots \\ \Psi_{i|k} \\ \vdots \end{bmatrix}, \quad T_{\Psi,B} = \begin{bmatrix} 0 & \cdots & 0 \\ \vdots & \cdots & \vdots \\ 1 & \cdots & \cdots \end{bmatrix}, \]

\[ S_{\Psi} = \begin{bmatrix} 0 \\ \Psi_{i|k} \\ \vdots \end{bmatrix}, \quad T_{\Psi,B}^{\top} = \begin{bmatrix} 1 & \cdots & \cdots \end{bmatrix}, \]

\[ \mathbf{L} = \begin{bmatrix} \xi_{N-0|0} & \cdots & \xi_{N-1|1} \\ \xi_{1-0|0} & \cdots & \xi_{1-1|1} \\ \vdots & \cdots & \vdots \\ \xi_{N-0|0} & \cdots & \xi_{N-1|1} \end{bmatrix}, \]

\[ \mathbf{K} = \text{diag}\{\gamma_{1|k}, \ldots , \gamma_{N-1|k}\} \otimes \xi_{N-0|0}, \quad \mathbf{M} = \text{diag}\{\mathbf{I}_{N \times N} \} \otimes \mathbf{M} \]

\[ \mathbf{x}_k - \mathbf{x}_k = \mathbf{S}_\Psi(x_k - \hat{x}_k) - \mathbf{T}_{\Psi,B}\mathbf{M}_k\mathbf{V}_k + \mathbf{T}_{\Psi,B}\mathbf{w}_k \] (8)

while (6) and (5b) give

\[ \mathbf{x}_k = \mathbf{S}_\Psi \hat{x}_k + \mathbf{T}_{\Psi,B} \mathbf{C}_k + \mathbf{L}_k \mathbf{z}_k + \mathbf{T}_{\Psi,B} \mathbf{M}_k \mathbf{z}_k \] (9a)

\[ \mathbf{u}_k = \mathbf{K}_k \mathbf{x}_k + c_k + \mathbf{L}_k \mathbf{z}_k \] (9b)

Clearly the predicted estimation error, state and control sequences in (8) and (9a,b) depend linearly on the decision variables \( \theta_k := (c_k, \mathbf{L}_k) \).

4.1 First and second moments of predicted sequences

In order to express the cost and constraints of problem (3) in terms of the parameterization introduced in Section 3, we derive in this section expressions for the means and variances of predicted state and control sequences.

First consider the state sequence \( \mathbf{x}_k \) of the plant (1a) and the state estimate update \( \hat{x}_k \) in step (ii) of the controller implementation in Section 3.1. By assumption we have \( \mathbb{E}\{x_0\} = \hat{x}_0 \) and \( \mathbb{E}\{w_k\} = 0 \), \( \mathbb{E}\{\xi_k\} = 0 \) for all \( k \geq 0 \), and hence the update of state estimate \( \hat{x}_k \) in step (ii)(b) ensures that

\[ \mathbb{E}\{x_k\} = \hat{x}_k \] (10)

for all \( k \geq 1 \). Furthermore, from (1a) we have \( x_k - \hat{x}_k = \mathbf{S}_{\Psi - k-1}(x_{k-1} - \hat{x}_{k-1}) + \gamma_k - A\mathbf{M}x_{k-1} + Dw_{k-1} \) for all \( k \geq 1 \). Let \( \Sigma_k \) denote the second moment of the state estimate error at time \( k \):

\[ \Sigma_k := \mathbb{E}\{ (x_k - \hat{x}_k) (x_k - \hat{x}_k)^\top \} \].

Then \( \Sigma_k \) evolves according to

\[ \Sigma_k = \mathbf{S}_{\Psi - k-1} \Sigma_{k-1} - \gamma_k - A\Sigma_{k-1}A^\top + D\Sigma_{w}D^\top \] (11)

for all \( k \geq 1 \), with initial condition \( \Sigma_0 \), and by Assumption 3 \( \Sigma_k \) remains upper bounded for all \( k \).
We first derive the first and second moments of the predicted state sequence $x_k$ and control sequence $u_k$:

**Proposition 2.** Let $\pi_k$, $\Pi_k$, and $\Omega_k$ be defined as $\pi_k = S \tilde{x}_k + T(\Phi,B) c_k$, $\Pi_k = T(\Phi,B) L_k + T(\Phi,A) M_k$, and $\Omega_k = E_k \left\{ \begin{bmatrix} x_k - \bar{x}_k \\ \zeta_k \end{bmatrix} \right\}$. Then

$$E_k \{ x_k \} = E_k \{ \bar{x}_k \} + \pi_k,$$

$$E_k \{ u_k \} = K E_k \{ \bar{x}_k \} + c_k = K \pi_k + c_k,$$

and

$$E_k \{ x_k x_k^\top \} = \pi_k \pi_k^\top + [I \ Pi_k] \Omega_k \begin{bmatrix} I \\ 0 \end{bmatrix}, \quad (13a)$$

$$E_k \{ u_k u_k^\top \} = (K \pi_k + c_k)(K \pi_k + c_k)^\top + [0 \ L_k + K \Pi_k] \Omega_k \begin{bmatrix} 0 \\ L_k + K \Pi_k \end{bmatrix}, \quad (13b)$$

Proof: From (8), (10) we have $E_k \{ x_k - \bar{x}_k \} = 0$. Therefore $\zeta_k = \Gamma_k C (x_k - \bar{x}_k)$ implies $E_k \{ \zeta_k \} = 0$ and (12a,b) follow from the expectations of (9a,b). To determine the second moments of $x_k$ and $u_k$, let

$$X_k := E_k \left\{ \begin{bmatrix} x_k - \bar{x}_k \\ \bar{x}_k \end{bmatrix} \right\}.$$

Then from (8) and (9a) we have

$$X_k = \begin{bmatrix} 0 & 0 & \pi_k & \Pi_k \\ I & 0 & \Omega_k & 0 \end{bmatrix} \begin{bmatrix} I \\ 0 \end{bmatrix}, \quad (14)$$

and (13a,b) follow from $E_k \{ x_k x_k^\top \} = [I \ I] X_k [I \ I]^\top$ and (9a,b), respectively. Since $\pi_k$ and $\Pi_k$ are linear in $(c_k, L_k)$ and $\Omega_k$ is independent of $(c_k, L_k)$, it is clear from (12a,b) and (13a,b) that the first moments of the predicted state and input sequences are linear in $\theta_k = (c_k, L_k)$ while their second moments are quadratic functions of $\theta_k$.

To determine $\Omega_k$, note that $x_k - \bar{x}_k$ and $\zeta_k$ can be written as

$$x_k - \bar{x}_k = F(\Gamma_k) q_k, \quad \zeta_k = G(\Gamma_k) q_k, \quad q_k = \begin{bmatrix} x_k - \bar{x}_k \\ v_k \\ w_k \end{bmatrix},$$

with $F(\Gamma_k) = [S \Phi - T(\Phi,A) M_k] \Gamma_k$ and $G(\Gamma_k) = \Gamma_k C F(\Gamma_k) + [0 \ \Gamma_k] 0$. So, by the law of total expectation,

$$\Omega_k = \sum_j \mathbb{E} \{q_k q_k^\top\} F(\Gamma_k)^\top G(\Gamma_k) \mathbb{P}\{\Gamma_k = \Gamma(j)\}, \quad (15)$$

where $E\{q_k q_k^\top\}$ is the block-diagonal matrix

$$E\{q_k q_k^\top\} = \text{diag}(\Sigma_k, \Sigma_v, \Sigma_w),$$

and where $\Sigma_j(j)$ for $j = 1, \ldots, 2^N$ enumerates the $2^N$ matrices with binary-valued diagonal elements defined by $\Gamma(j)^{(1)} = 0$, $\Gamma(j)^{(2)} = \text{diag}(0, \ldots, 0, 1) \otimes I_{n_x n_x}$, $\ldots$, $\Gamma(j)^{(2^N-1)} = \text{diag}(1, \ldots, 1, 0) \otimes I_{n_x n_x}$, $\Gamma(j)^{(2^N)} = I$.  

**Remark 3.** $\Omega_k$ in (15) can be computed conveniently via $\text{vec}(\Omega_k) = 

$$= \sum_{i=N}^{\infty} \beta^i \{X_{i+1|k} - E\{\hat{D}(\gamma)\} [\Sigma_v \Sigma_w] \hat{D}(\gamma)\}$$

= $\beta^{-1} (P_k - \beta N X_N|k) - \frac{\beta N}{1 - \beta} E\{\hat{D}(\gamma)\} [\Sigma_v \Sigma_w] \hat{D}(\gamma)\}$

and the terminal term $f_N(\theta_k, \bar{x}_k, \Sigma_k)$ in (17) is equal to

$$\text{tr}\left\{ \frac{Q}{Q + K R K} P_k \right\}$$

with the additional constraint

$$P_k \succeq \beta \mathbb{E}\{\hat{D}(\gamma) P_k \hat{D}(\gamma)^\top\} + \beta N X_N|k + \frac{\beta N+1}{1 - \beta} E\{\hat{D}(\gamma)\} [\Sigma_v \Sigma_w] \hat{D}(\gamma)\}, \quad (18)$$
Using (16) and Schur complements, (18) can be expressed as a linear matrix inequality in \( \theta_k = (c_k, L_k) \) and \( P_k \).

Re-writing the constraints of problem (3) using the matrix, \( X_{i|k} \), of second moments yields the condition
\[
\sum_{i=0}^{\beta} \text{tr}[(1_{2 \times 2} \otimes H^T H) X_{i|k}] \leq \mu_k,
\]
which is equivalent to the constraint
\[
\text{tr}(H_i X_k) + \text{tr}[(1_{2 \times 2} \otimes H^T H) P_k] \leq \mu_k
\]
where \( H_\beta = 1_{2 \times 2} \otimes \text{diag}(H^T H, \beta H^T H, \ldots, \beta^{N-1} H^T H) \).

The expressions for the cost and constraints in (17)-(19) allow the optimization (3) to be formulated as
\[
\theta_k^* = \arg \min_{\theta_k, P_k} \text{tr}(Q \theta_k) + \text{tr}(R \theta_k) + \text{tr} \left( \begin{bmatrix} Q & Q^T \end{bmatrix} P_k \right)
\]
s.t. (18), (19).

**Remark 4.** Problem (20) can be expressed as a semidefinite program in the variables \( \theta_k = (c_k, L_k) \) and \( P_k \) using (13b), (14) and (16). Alternatively, we can eliminate \( P_k \) by (20) from the solution of the Lyapunov equation
\[
P_k = \beta \mathbb{E} \left[ \tilde{W}(\gamma) P_k \tilde{W}(\gamma) \right] + \mathbb{E} \text{ for given } \Xi = \Xi^T
\]
from vector (20) by using standard matrix vectorization identities, as a convex quadratic program in \( \theta_k = (c_k, L_k) \) with a single quadratic constraint.

### 6. CLOSED LOOP PROPERTIES

This section considers the performance of the closed loop system (1) with the control law of Section 3.1. We use the solution \( \theta_k^* = (c_k^*, L_k^*) \) of (3) at time \( k \) to construct a feasible, but possibly suboptimal, solution for (3) at time \( k+1 \) (i.e. given \( U_k, L_k \)), which we denote \( \theta_{k+1} = (c_{k+1}, L_{k+1})^o \), where

\[
\begin{align*}
c_{k+1}^o &= \begin{bmatrix} c_{k+1}^o \end{bmatrix} := \begin{bmatrix} c_{1,k}^o \end{bmatrix} + \begin{bmatrix} L_{1,0,k}^o \end{bmatrix} \gamma_k(y_k - C\tilde{x}_k), \quad (21a) \\
L_{k+1}^o &= \begin{bmatrix} L_{1,1,k}^o \end{bmatrix} \ldots \begin{bmatrix} L_{N-1,1,k}^o \end{bmatrix} \ldots \begin{bmatrix} L_{N-1,N-1,k}^o \end{bmatrix} \begin{bmatrix} \cdots \end{bmatrix} \begin{bmatrix} 0 \end{bmatrix}. \quad (21b)
\end{align*}
\]

Following Yan et al. (2018), we define the constraint threshold \( \mu_k \) in (3) for all \( k > 0 \) in terms of \( \theta_k^* \). This ensures recursive feasibility of the MPC optimization without requiring bounds on the noise \( \eta_k \) and disturbance \( w_k \). Thus
\[
\mu_k := \left\{ \begin{array}{ll}
0 & k = 0 \\
\text{tr}(H_k X_k) + \text{tr}[(1_{2 \times 2} \otimes H^T H) P_k] & k > 0
\end{array} \right.
\]
where
\[
P_k^o = \beta \mathbb{E} \left[ \tilde{W}(\gamma) P_k^o \tilde{W}(\gamma) \right]
\]
\[
+ \beta^{N+1} \mathbb{E} \tilde{W}(\gamma) \sum_{i=0}^{\infty} \Xi \tilde{W}(\gamma)
\]
\[
\begin{bmatrix}
0 & 0 \\
0 & \pi^2_k \Xi
\end{bmatrix} \quad + \begin{bmatrix} I & 0 \\
0 & \Pi_k^N \end{bmatrix} \quad \Omega_k \quad \begin{bmatrix} I & 0 \\
0 & \Pi_k \end{bmatrix}^T
\]
\[
X_k^o = \begin{bmatrix}
0 & 0 \\
0 & \pi^2_k \Xi^N_k
\end{bmatrix} + \begin{bmatrix} I & 0 \\
0 & \Pi_k^N \end{bmatrix} \quad \Omega_k \quad \begin{bmatrix} I & 0 \\
0 & \Pi_k^N \end{bmatrix}^T
\]

with \( \pi_k^0 = S_{\phi} \hat{x}_k + T_{(\phi,B)} c_k^0, \quad \Pi_k^o = T_{(\phi,A)} L_k^0 + T_{(\phi,A)} M \).

**Theorem 5.** If problem (3) is feasible at \( k = 0 \), then (3) remains feasible for all \( k > 0 \) and the state of (1) under the control law of Section 3.1 satisfies
\[
\sum_{k=0}^{\infty} \beta^k \mathbb{E} \left[ \| H x_k \|_2^2 \right] \leq \epsilon.
\]

**Proof:** The definition (22) of \( \mu_k \) trivially ensures feasibility for all \( k > 0 \). The definitions (21a,b) ensure that, at time \( k \) (given \( U_k-1, L_{k-1} \)), the distributions of the state and control sequences \( \{x_{i|k+1}\}_\infty \) and \( \{u_{i|k+1}\}_\infty \) are identical to the distributions of \( \{x_{i+1|k}\}_\infty \) and \( \{u_{i+1|k}\}_\infty \). Therefore
\[
\sum_{i=0}^{\infty} \beta^i \mathbb{E} \left[ \| H x_{i+1|k} \|_2^2 \right] = \text{tr}(H_k X_k) + \text{tr}[(1_{2 \times 2} \otimes H^T H) P_k]
\]
implies
\[
\beta \mathbb{E} \{\| H x_{k+1} \|_2^2 \} \leq \mu_k - \lim_{i \rightarrow \infty} \beta^i \mathbb{E} \{\| H x_{k+1} \|_2^2 \} \leq \mu_k
\]
for all \( k \geq 0 \).

**Corollary 6.** Let \( J_k := J(\theta_k^*, \hat{x}_k, \Sigma_k) \) denote the optimal value of the objective in (3). Then under the control law of Section 3.1, the trajectories of (1) satisfy
\[
\sum_{k=0}^{\infty} \beta^k \mathbb{E} \left[ \| x_k \|_2^2 + \| u_k \|_R^2 \right] \leq J_0.
\]

**Proof:** Applying the same argument used in the proof of Theorem 5 to the definition of the objective in (3) yields
\[
\beta \mathbb{E} \{J(\theta_{k+1}^*, \hat{x}_{k+1}, \Sigma_{k+1})\} = J_k - \mathbb{E} \{\| x_{k+1} \|_2 + \| u_k \|_R \},
\]
and since \( J_k \leq J(\theta_k^*, \hat{x}_k, \Sigma_k) \forall k \) by optimality, the bound in (24) follows.

### 7. NUMERICAL EXAMPLES

This section gives a numerical example to demonstrate that the closed loop system satisfies (23) and (24) and to compare with the unconstrained optimal LQG controller. We consider a system obtained by discretising a linearised continuous time model of a double inverted pendulum with a sample time of 0.01 s as in (Kwakernaak and Systd, 1985). The system matrices are
\[
A = \begin{bmatrix}
1.0005 & 0.01 \\
-0.0005 & 1.0005
\end{bmatrix}, \quad B = \begin{bmatrix}
0.0005 & -0.0005 \\
0.0006 & -0.0005
\end{bmatrix}, \quad C = \begin{bmatrix}
1 & 0 \\
0 & 1
\end{bmatrix}, \quad D = I,
\]
and \( \omega_k \sim \mathcal{N}(0, Q) \), \( V_k \sim \mathcal{N}(0, \Sigma) \), \( \lambda = 0.6 \). Here \( \Sigma_\omega = \text{diag}(0.5, 0.2, 0.9, 0.3) \) and \( \Sigma_\nu = 1.1I \). Initial conditions are given by
\[
x_0 = \begin{bmatrix}
-0.8 \\
0.5
\end{bmatrix}, \quad \bar{x}_0 = \begin{bmatrix}
0.1 \\
0.05
\end{bmatrix}, \quad \Sigma_0 = \begin{bmatrix}
0.5 & -0.5 \\
-0.5 & 0.5
\end{bmatrix}, \quad H = \begin{bmatrix}
0 & 0.1 \\
0.1 & -0.1
\end{bmatrix}.
\]
The constraint of (2) is defined by \( \beta = 0.95, \epsilon = 111 \) and
\[
H = \begin{bmatrix}
0 & 0.1 \\
0.1 & -0.1
\end{bmatrix}.
\]

The weighting matrices in the cost function of (2) are given by \( Q = \text{diag}(10, 0.1, 0.1, 0.1) \), \( R = 10^{-4} I \). We choose a prediction horizon \( N = 5 \), \( K \) as the unconstrained LQ-optimal, \( K_{LQ} \), with respect to \( (A, B, Q, R) \) and \( M = \).
\[ \Sigma C^\top (C\Sigma C^\top + \Sigma_v)^{-1}, \] where \( \Sigma \) is the solution of the algebraic Riccati equation
\[ \Sigma = A\Sigma A^\top + \Sigma_w - \lambda A\Sigma C^\top (C\Sigma C^\top + \Sigma_v)^{-1} C\Sigma A^\top. \]

Using the above information, we solve problem (20) and obtain \( J_0 = 2.368 \times 10^4 \).

**Simulation A:** To estimate empirically the LHS of (23) and (24), we consider their average values over 10^3 simulations, each of which has a length of 500 time steps. This gives \( \sum_{k=0}^{\infty} \beta^k E\{\|Hx_k\|^2\} \) and \( \sum_{k=0}^{\infty} \beta^k E\{\|x_k\|^2 + \|u_k\|^2 \} \) as 104.7 and 4.774 \times 10^3 respectively. Therefore, these estimates agree with the bound (23) and (24). Moreover, \( \beta^{500} = 7.3 \times 10^{-12} \), so a further increase in the horizon length has negligible effect on these estimates.

**Simulation B:** To compare with the above results, we run the same number of simulations with the same \{\omega_k\}, \{v_k\}, \{\gamma_k\} sequences using the unconstrained optimal LQG controller, where \( u_k = K_L Q x_k \) and the estimator gain is time-varying and given by \( M = \Sigma_k C^\top (C\Sigma_k C^\top + \Sigma_v)^{-1} \). Here \( \Sigma_k \) evolves as
\[ \Sigma_{k+1} = A\Sigma_k A^\top + \Sigma_w - \gamma_k A\Sigma_k C^\top (C\Sigma_k C^\top + \Sigma_v)^{-1} C\Sigma_k A^\top. \]
This gives \( \sum_{k=0}^{\infty} \beta^k E\{\|Hx_k\|^2\} \) as 123.8, violating the bound (23), and \( \sum_{k=0}^{\infty} \beta^k E\{\|x_k\|^2 + \|u_k\|^2 \} \) as 3.626 \times 10^4, which is smaller than that in Simulation A, as expected.

### 8. CONCLUSION

This paper describes an output feedback MPC algorithm for linear discrete time systems with additive disturbances and noisy sensor measurements transmitted over a packet-dropping communication channel. By designing a control policy with an affine dependence on future observations, we provide a convex formulation of a stochastic quadratic regulation problem subject to a discounted expectation constraint. Our controller parameterization ensures recursive feasibility of the MPC optimization problem and ensures a cost bound and constraint satisfaction in closed loop operation. Future work will explore interconnections between conditions for mean square stability of the MPC law and the values of the packet loss probability and the discount factor in the receding horizon optimization.

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