

## OPTIMAL CONTROL UNDER PARTIAL OBSERVATIONS AND STOCHASTIC UNIFORM OBSERVABILITY

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ABSTRACT. This paper discuss linear quadratic control problem for stochastic differential systems with partial observations. Following [4] and using the results in [8] concerning the Riccati equation, we apply the well known separation principle to obtain a solution of the optimal control problem considered.

## 1. Optimal control under partial observations

Let  $H, U, V, \dim(V) < \infty$  be separable real Hilbert spaces. Throughout this section we will assume that the next hypothesis are satisfied:

Throughout this chapter we assume the following hypotheses:

(G1) U(t,s) is a strong evolution operator generated by the family  $A(t), t \in [0,\infty)$ ; there exists a sequence  $\{A_n\}_{n \in \mathbb{N}} \subset C_s([0,\infty), L(H))$  such that for every  $n \in \mathbb{N}$ , the family  $\{A_n(t)\}_{t \ge 0}$  generates the strong evolution operator  $U_n(t,s)$  and  $U_n(t,s)x \to U(t,s)x, x \in H$  uniformly on

bounded subsets of  $\Delta$ . The families  $A^*(t), A^*_n(t), n \in \mathbb{N}, t \in [0, \infty)$  satisfy the hypothesis (G1) and we will say that G1 (A<sup>\*</sup>) holds.

(G2):  $B \in C_b(\mathbf{R}_+, L(U, H)), B^* \in C_b(\mathbf{R}_+, L(H, U)), C \in C_b(\mathbf{R}_+, L(H, V)), C^* \in C_b(\mathbf{R}_+, L(V, H))$ , N, G, G<sup>\*</sup>  $\in C_b(\mathbf{R}_+, L(H)), \overline{V} \in C([0, \infty), L(V)), V(t)$  is nonsingular for all  $t \in [0, \infty)$  and  $K \in C_b(\mathbf{R}_+, L(U))$  is uniformly positive, that is there exists  $\delta > 0$  such that  $K(t) \ge \delta I$ , for all  $t \in \mathbf{R}_+$ .

We consider the following stochastic system with control and partial observations (1) dy(t) = A(t)y(t)dt + B(t)u(t)dt + G(t)dw(t),

$$\mathbf{y}(\mathbf{0}) = \mathbf{y}_0 \in \mathbf{L}^2_{\mathbf{s}}(\mathbf{H});$$

(2)  $dz(t) = C(t)y(t)dt + \overline{V}(t)dv(t), z(0) = 0,$ 

where w(t),v(t),t  $\geq 0$  are real valued Wiener processes and  $y_0$  is Gaussian with mean  $m_0$  and covariance  $Q_0$  and  $y_0$ , w(t),v(t),t  $\geq 0$  are mutually independent. We also introduce the cost functional

(3) 
$$J(u) = \overline{\lim}_{t \to \infty} \frac{1}{t} E \int_{0}^{t} ||N(s)y(s)||^{2} + \langle K(s)u(s), u(s) \rangle ds$$

Our problem is to minimize J(u) over a class of admissible controls u(t), which are adapted to the  $\sigma$ -algebra generated by the observations  $z(s), s \in [0,t]$ . We will define the set of admissible controls later. Now, we recall some basic results on filtering theory. Let  $Z_t$  be the  $\sigma$ -algebra generated by  $z(s), s \in [0,t]$  and let us consider the system

 $(4) dy(t) = A(t)y(t)dt + G(t)dw(t), y(0) = y_0$ 

$$(5) dz(t) = Cy(t) dt + V(t) dv(t), z(0) = 0$$

The filtering problem consists in estimating the state y(t) based on the observation process  $z(s), 0 \le s \le t$ . The most popular, optimal in the mean square sense, filtering estimator of y(t) is its projection onto  $L^2(\Omega, Z_t, P, H)$ . This estimator is called *the best global estimator* of y given  $z(s), 0 \le s \le t$  and is equal to the conditional expectation  $E[y(t)|Z_t]$  [6]. The conditional expectation, as a function of  $z(s), s \in [0, t]$ , may have too complicated structure. Therefore, especially in engineering applications, it makes sense to use a linear function  $\hat{y}(t)$  of  $z(s), s \in [0, t]$ , minimizing the mean square error  $E||y(t) - \hat{y}(t)||^2$  in a class of linear filtering estimates. Then we define below the best affine estimator of y(t).

Let T > 0 be fixed and let  $z \in C([0,T], L^2(\Omega, \mathbf{F}, P, V)), y \in L^2(\Omega, P, H)$ . We denote by  $H_z^t$ the closure in  $L^2(\Omega, P, H)$  of the linear space generated by the set  $\{x + L(z(s_j)), x \in H, L \in L(V, H), s_j \in [0, t]\}$ . Obviously  $H_z^t$  is the analogue of the Hilbert space  $H_y$  defined in the time invariant case and it is a Hilbert subspace of  $L^2(\Omega, P, H)$ . If  $P_z^t$  denotes the projection on  $L^2(\Omega, P, H)$  upon  $H_z^t$  then  $P_z^t(y)$  is called *the best affine estimator* of  $y \in L^2(\Omega, P, H)$  given  $\{z(s), 0 \le s \le t\}$ . As in the discrete-time case we note that if we set  $\overline{z}(t) = z(t) - E(z(t))$ , then  $H_z^t = H_{\overline{z}}^t$ .

If  $H_0 = \{y \in L^2(\Omega, P, H), E(y) = 0\}$  is the Hilbert subspace of  $L^2(\Omega, P, H)$  and  $H_{0,\overline{z}}^t$  is the closure in  $L^2(\Omega, P, H)$  of the linear space generated by the set  $\{L(z(s_j)), L \in L(V, H), s_j \in [0, t]\}$  then  $P_{0,\overline{z}}^t(y)$  will denote the projection on  $L^2(\Omega, P, H)$  upon  $H_{0,\overline{z}}^t$ . Obviously  $H_{0,\overline{z}}^t \subset H_z^t$ . Then  $P_{0,\overline{z}}^t(y)$  is called the best linear estimator of  $L^2(\Omega, P, H) y$  given  $\{\overline{z}(s), 0 \le s \le t\}$ . It is clear that  $P_z^t(y) = E(y) + P_{0,\overline{z}}^t(y)$  and consequently the problem of finding the best affine estimator reduces to that of finding the best linear estimator [7]. We note here that the linear estimates are easier to calculate, but unlike the best global estimates they need not always exist.

It is known that if  $y \in L^2(\Omega, P, H), z \in L^2(\Omega, P, V)$  are Gaussian random variables and the best linear estimate of y given z exists, then it coincides with the best global estimate [2].

As in the discrete-time case, the filtering problem for (4), (5) is to find the best affine estimate  $\hat{y}(t) = P_z^t(y), t \ge 0$ . It is well known [2], [1], [7] that, because of the Gaussian property of the processes, the best affine estimate of the solution y(t) of (4), (5) coincides with the best global estimator  $E[y(t)|Z_t]$ . Moreover, it is the unique mild solution of

$$(6) \hat{dy}(t) = A(t)\hat{y}(t)dt + P(t)C^*(t)\left[\overline{V}(t)\overline{V}^*(t)\right]^{-1}d\eta(t),$$

 $(7) \dot{\mathbf{y}}(0) = \mathbf{E}(\mathbf{y}_0),$ 

where  $\eta~$  is the innovation process defined by

$$(8) d\eta(t) = dz(t) - C(t) y(t) dt$$

and P(t) is the covariance of the error process  $e(t) = y(t) - \hat{y}(t)$ . A rather surprising properties are the following: the innovation process  $\eta(t)$  is a finite dimensional Wiener process with the covariance  $t\overline{V}(t)\overline{V}(t)^*$  relative to the  $\sigma$ -algebra  $Z_t$ ;  $H_{0,\overline{z}}^t = H_{0,\overline{\eta}}^t$  [2], [7]. Also it is known that the covariance of the error process is the unique mild solution of the following Riccati equation [2], [5]

(9) 
$$P'(t) = A(t)P(t) + P(t)A^{*}(t) + G(t)G^{*}(t) - P(t)C^{*}(t)\left[\overline{V}(t)\overline{V}^{*}(t)\right]^{-1}C(t)P(t)$$
  
(10)  $P(0) = P_{0} = cov(e_{0}, e_{0}), e_{0} = y_{0} - \overline{y}_{0}.$ 

The next result shows that, under stabilizability conditions, the above Riccati equation has a bounded on  $\mathbf{R}_+$  solution. We recall here that the pair  $\{A^* : C^*\}$  is *stabilizable* iff there exists  $F \in C_b([0,\infty), L(H, V))$  such that  $\{A^* + C^*F\}$  is uniformly exponentially stable.

**Theorem 1** [4] Assume  $\{A^* : C^*\}$  is stabilizable. The solution P(t) of (9)-(10) is bounded on  $\mathbf{R}_+$ .

Returning to the quadratic control problem, we now define the class of admissible controls  $\mathcal{U}$ . Let  $\Gamma_t$  be the  $\sigma$  - algebra generated by  $\eta(s), s \in [0, t]$ , where  $\eta$  is the innovation process given by (8).

Following [4], [5], [7] we that  $\mathcal{U}$  is the set of all controls  $u \in L^2_{loc}([0,\infty) \times \Omega, U)$  that are  $\mathbf{F}_t$  - adapted and satisfy the conditions  $u(t) \in L^2(\Omega, Z_t, P, H) \cap L^2(\Omega, \Gamma_t, P, H)$  for almost all t,  $\overline{\lim_{t\to\infty} \frac{1}{t}} E \int_0^t ||u(s)||^2 ds < \infty$ ,  $\sup_{t\geq 0} E ||y(s)||^2 < \infty$ .

If  $u \in U$ , we associate to the system (6), (7) the following control system

$$(11)d\hat{y}(t) = A(t)\hat{y}(t)dt + B(t)u(t)dt + P(t)C^{*}(t)\left[\overline{V}(t)\overline{V}^{*}(t)\right]^{-1}d\eta(t),$$

 $(12) \mathbf{y}(0) = \mathbf{E}(\mathbf{y}_0)$ 

Denoting by  $\hat{y}_u$  the solution of the above system, then  $\hat{y} - \hat{y}_u$  is the unique solution of

the system

(13) 
$$dx(t) = A(t)x(t)dt + B(t)u(t)dt, x(0) = 0$$

Choosing the same control u, we consider the unique mild solutions  $y_u$  and y of (4) and (1) respectively, and we see that y- $y_u$  is also the unique mild solution (13). Therefore  $y - y_u = \hat{y} - \hat{y}_u$  and  $y_u(t) - \hat{y}_u(t) = e(t)$ . An easy computation shows that

$$E \| \mathbf{N}(t) \mathbf{y}_{u}(t) \|^{2} = \mathrm{Tr}\mathbf{N}(t) \operatorname{cov}\left(\mathbf{e}(t), \mathbf{e}(t)\right) \mathbf{N}^{*}(t) + 2E \left\langle \mathbf{N}(t) \hat{\mathbf{y}}_{u}(t), \mathbf{e}(t) \right\rangle + E \| \mathbf{N}(t) \hat{\mathbf{y}}_{u}(t) \|^{2}.$$
  
If  $U(t,s)$  is the evolution operator generated by  $A$  then

$$\hat{y}_{u}(t) = U(t,r)\overline{y}_{0} + \int_{0}^{t} U(t,r)B(r)u(r)dr +$$

$$\int_{0}^{t} U(t,r)P(r)C^{*}(r) \Big[V(r)V^{*}(r)\Big]^{-1}d\eta(r) = T_{1} + T_{2} + T_{3}.$$
We note that  $T_{3} \in H_{0,\overline{n}}^{t}$  and  $H_{0,\overline{n}}^{t} = H_{0,\overline{z}}^{t} \subset H_{z}^{t}$ . Since  $e(t) \in (H_{z}^{t})^{\perp}$  we deduce

$$E\langle T_3, e(t) \rangle = 0$$
. Also  $T_1 \in H_z^t$  and  $E\langle T_1, e(t) \rangle = 0$ . Further  $\int_0^t U(t, r)B(r)u(r)dr$  is  $Z_t$   
measurable and therefore  $E\langle T_2, e(t) \rangle = E(E[\langle T_2, e(t) \rangle |_{Z_t}]) = E[\langle T_2, E[e(t) |_{Z_t}] \rangle] = 0$ . We just have proved that  $E\langle \hat{y}_u(t), e(t) \rangle = 0$ . Hence  $2E\langle N(t)\hat{y}_u(t), e(t) \rangle = 0$  and

(14) 
$$E \| N(t)y_u(t) \|^2 = TrN(t)P(t)N^*(t) + E \| N(t)\hat{y}_u(t) \|^2$$
,

where P(t) is the solution of (9)-(10). Let now introduce the cost functional

(15) 
$$\widehat{J}(u) = \overline{\lim}_{t \to \infty} \frac{1}{t} E \int_{0}^{t} \left\| N(s) \widehat{y}_{u}(s) \right\|^{2} + \left\langle K(s)u(s), u(s) \right\rangle ds.$$

If P(t) is bounded on  $\mathbf{R}_+$  we deduce by (14)

(16) 
$$J(u) = \widehat{J}(u) + \overline{\lim}_{t \to \infty} \frac{1}{t} \int_{0}^{t} TrN(s)P(s)N^{*}(s)ds$$

Now it is clear that the optimal control in the class  $\mathcal{U}$ , which minimize (15) subject to (11)-(12) is also optimal for our control problem with partial observations (separation principle). Therefore, we can solve the linear quadratic control problem with complete observations (11)-(12), (15). Let us consider the Riccati equation

(17) 
$$R'(t) + A^{*}(t)R(t) + R(t)A(t)$$

$$+N(t)N^{*}(t) - R(t)B(t)[K(t)]^{-1}B^{*}(t)R(t) = 0$$

We recall here that a global solution R(t) of (17) is stabilizing for  $\{A : B\}$  iff  $\{A - B[K(t)]^{-1}B^*R\}$  is uniformly exponentially stable. The following result is known:

**Proposition 2** [4,8] Assume  $\{A : B\}$  is stabilizable and  $\{A; N\}$  is either uniformly

observable or detectable. Then the Riccati equation (17) has a unique nonnegative, bounded on  $\mathbf{R}_+$  and stabilizing solution R(t).

Before to prove the main result of this section it is useful to introduce the following approximating systems

(18) 
$$\hat{R}_{n}(t) + A_{n}^{*}(t)R_{n}(t) + R_{n}(t)A_{n}(t) + N(t)N^{*}(t) - R_{n}(t)B(t)[K(t)]^{-1}B^{*}(t)R_{n}(t) = 0,$$
  
(19)  $\hat{dy}_{n}(t) = A_{n}(t)\hat{y}_{n}(t)dt + B(t)u(t)dt + P(t)C^{*}(t)[\overline{V}(t)\overline{V}^{*}(t)]^{-1}d\eta(t), \hat{y}_{n}(0) = \overline{y}_{0}, n \in \mathbb{N}.$ 

Let  $Q \in L^+(H)$ . It is known [5] that (18) (respectively (17)) with the final condition  $R_n(T) = Q$  (respectively R(T) = Q) has a unique classical (respectively mild) solution  $R_n(T,s;Q)$ . Moreover,  $Q_n(T,s;R)x \xrightarrow[n\to\infty]{} Q(T,s;R)x$ , uniformly on [0,T]. Analogously, the

system (19)-(20) has unique strong solution  $\hat{y}_{u}^{(n)}(t)$ , which converges to the unique mild solution  $\hat{y}_{u}(t)$  of (11)-(12) uniformly on [0,T].

**Theorem 3** Assume that  $\{A^* : C^*\}$  is stabilizable and the hypotheses of the above proposition are satisfied. Then the optimal control for the problem (11)-(15) is given by the feedback law  $\tilde{u}(t) = -[K(t)]^{-1}B^*(t)R(t)\hat{y}_{\tilde{u}}(t)$ , where *R* is the unique bounded and nonnegative solution of (17). The optimal cost is

(20) 
$$\hat{J}(\tilde{u}) = \overline{\lim}_{t \to \infty} \frac{1}{t} \int_{0}^{t} TrR(s)P(s)C^{*}(s) \left[\overline{V}(s)\overline{V}^{*}(s)\right]^{-1}C(s)P(s)ds.$$

Moreover, the control  $\tilde{u}$  is also optimal for the control problem with partial observations (1)-(2), (3) and

$$\min_{\mathbf{u}\in\mathbf{U}} \mathbf{J}(\mathbf{u}) = \mathbf{J}(\tilde{\mathbf{u}}) = \hat{\mathbf{J}}(\tilde{\mathbf{u}}) + \overline{\lim}_{t\to\infty} \frac{1}{t} \int_{0}^{t} \mathrm{TrN}(s) \mathbf{P}(s) \mathbf{N}^{*}(s) \mathrm{d}s.$$

**Proof.** Let R(t) be the unique global solution of (17). If  $R_n(s) = R_n(t,s,R(t))$  is the solution of (18), then we consider the function  $F_n(s,x) = \langle R_n(s)x,x \rangle$  which is continuous together its partial derivatives  $F_{n,s}$ ,  $F_{n,x}$ ,  $F_{n,xx}$  on  $[0,\infty) \times H$ . Let  $u \in U$  and  $\hat{y}_u(s)$  be its response. Using Ito's formula for  $F_n(s,x)$  and the strong solution  $\hat{y}_u^{(n)}(s)$  of (19) and taking expectations we get

$$E \left\langle R_{n}(t)\hat{y}_{u}^{(n)}(t), \hat{y}_{u}^{(n)}(t) \right\rangle - \left\langle R_{n}(0)\overline{y}_{0}, \overline{y}_{0} \right\rangle = -E \int_{0}^{t} \left\| N(s)\hat{y}_{u}^{(n)}(s) \right\|^{2} + \left\langle K(s)u(s), u(s) \right\rangle ds$$
$$+E \int_{0}^{t} \left\| K(s)^{1/2} \left[ u(s) + \left[ K(s) \right]^{-1} B^{*}(s) R_{n}(s)\hat{y}_{u}^{(n)}(u) \right] \right\|^{2} ds$$
$$+\int_{0}^{t} TrR_{n}(s)P(s)C^{*}(s) \left[ \overline{V}(s)\overline{V}^{*}(s) \right]^{-1}C(s)P(s) ds.$$

We first note that  $R_n(s) \xrightarrow[n \to \infty]{} R(s)$  uniformly on [0,t]. Letting  $n \to \infty$  in the above relation and using the Dominated Convergence Theorem of Lebesgue we get

$$E \left\langle R(t)\hat{y}_{u}(t), \hat{y}_{u}(t) \right\rangle - \left\langle R(0)\overline{y}_{0}, \overline{y}_{0} \right\rangle = -E \int_{0}^{t} \left\| N(s)\hat{y}_{u}(s) \right\|^{2} + \left\langle K(s)u(s), u(s) \right\rangle ds$$
$$+E \int_{0}^{t} \left\| K(s)^{1/2} \left[ u(s) + \left[ K(s) \right]^{-1} B^{*}(s) R(s)\hat{y}_{u}(u) \right] \right\|^{2} ds$$
$$+\int_{0}^{t} TrR(s) P(s) C^{*}(s) \left[ \overline{V}(s) \overline{V}^{*}(s) \right]^{-1} C(s) P(s) ds.$$

We make use of the boundedness of R(t) and we easily deduce that

$$\hat{J}(u) = \overline{\lim}_{t \to \infty} \frac{1}{t} \int_{0}^{t} TrR(s)P(s)C^{*}(s) \left[\overline{V}(s)\overline{V}^{*}(s)\right]^{-1}C(s)P(s)ds$$
$$+\overline{\lim}_{t \to \infty} \frac{1}{t}E\int_{0}^{t} \left\|K(s)^{1/2} \left[u(s) + \left[K(s)\right]^{-1}B^{*}(s)R(s)\hat{y}_{u}(u)\right]\right\|^{2}ds.$$

It is not difficult to see that  $\tilde{u}(s) = -[K(s)]^{-1} B^*(s) R(s) \hat{y}_u(u), s \ge 0$  belongs to  $\mathcal{U}$  and minimize  $\hat{J}(u)$  in the class of admissible controls. Obviously, (20) follows by (16). The proof is complete.

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