

# Filtering and Stochastic Control: A Historical Perspective

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In this article we attempt to give a historical account of the main ideas leading to the development of non-linear filtering and stochastic control as we know it today.

The article contains six sections. In the next section we present a development of linear filtering theory, beginning with Wiener-Kolmogoroff filtering and ending with Kalman filtering. The method of development is the innovations method as originally proposed by Bode and Shannon and later presented in its modern form by Kailath. The third section is concerned with the Linear-Quadratic-Gaussian problem of stochastic control. Here we give a discussion of the separation theorem which states that for this problem the optimal stochastic control can be constructed by solving separately a state estimation problem and a deterministic optimal control problem. Many of the ideas presented here generalize to the non-linear situation. The fourth section gives a reasonably detailed discussion of non-linear filtering, again from the innovations viewpoint. Finally, the fifth and sixth sections are concerned with optimal stochastic control. The general method of discussing these problems is Dynamic Programming.

We have chosen to develop the subject in continuous time. In order to obtain correct results for nonlinear stochastic problems in continuous time it is essential that the modern language and theory of stochastic processes and stochastic differential equations be used. The book of Wong [5] is the preferred text. Some of this language is summarized in the third section.

## Wiener and Kalman Filtering

In order to introduce the main ideas of non-linear filtering we first consider linear filtering theory. A rather comprehensive survey of linear filtering theory was undertaken by Kailath in [1] and therefore we shall only expose those ideas which generalize to the non-linear situation. Suppose we have a signal process  $(z_t)$  and an orthogonal increment process  $(w_t)$ , the noise process and we have the observation equation

$$y_t = \int_0^t z_s ds + w_t \quad (1)$$

Note that if  $w_t$  is Brownian motion then this represents the observation

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$$\dot{y}_t = z_t + \eta_t \quad (2)$$

where  $\eta_t$  is the formal (distributional) derivative of Brownian motion and hence it is white noise. We make the following assumptions.

- (A1)  $(w_t)$  has stationary orthogonal increments
- (A2)  $(z_t)$  is a second-order q.m. continuous process
- (A3) For  $\forall s$  and  $t > s$

$$(w_t - w_s) \perp H_s^{w,z}$$

where  $H_s^{w,z}$  is the Hilbert space spanned by  $(w_\tau, z_\tau \mid \tau \leq s)$ .

The last assumption is a causality requirement but includes situations where the signal  $z_s$  may be influenced by past observations as would typically arise in feedback control problems. A slightly stronger assumption is

$$(A3)' H^w \perp H^z$$

which states that the signal and noise are uncorrelated, a situation which often arises in communication problems. The situation which Wiener considered corresponds to (2), where he assumed that  $(z_t)$  is a stationary, second-order, q.m. continuous process.

The *filtering* problem is to obtain the best linear estimate  $\hat{z}_t$  of  $z_t$  based on the past observations  $(y_s \mid s \leq t)$ . There are two other problems of interest, namely, *prediction*, when we are interested in the best linear estimate  $\hat{z}_r$ ,  $r > t$  based on observations  $(y_s \mid s \leq t)$  and *smoothing*, where we require obtaining the best linear estimate  $\hat{z}_r$ ,  $r < t$  based on observations  $(y_s \mid s \leq t)$ . Abstractly, the solution to the problem of filtering corresponds to explicitly computing

$$\hat{z}_t = P_t^y(z_t) \quad (3)$$

where  $P_t^y$  is the projection operator onto the Hilbert space  $H_t^y$ . We proceed to outline the solution using a method originally proposed by Bode and Shannon [2] and later presented in modern form by Kailath [3]. For a textbook account see Davis [4] and Wong [5], which we largely follow.

Let us operate under the assumption (A3)', although all the results are true under the weaker assumption (A3). The key to obtaining a solution is the introduction of the innovations process

$$v_t = y_t - \int_0^t \hat{z}_s ds \quad (4)$$

The following facts about the innovations process can be proved:

(F1)  $v_t$  is an orthogonal increment process.

(F2)  $\forall s, \forall t > s$

$$v_t - v_s \perp H_s^y \text{ and}$$

$$\text{cov}(v_t) = \text{cov}(w_t)$$

(F3)  $H_t^y = H_t^y$ .

The name ‘‘innovations’’ originates in the fact that the optimum filter extracts the maximal probabilistic information from the observations in the sense that what remains is essentially equivalent to the noise present in the observation. Furthermore, (F3) states that the innovations process contains the same information as the observations. This can be proved by showing that the linear transformation relating the observations and innovations is causal and causally invertible. As we shall see later, these results are true in a much more general context. To proceed further, we need a concrete representation of vectors residing in the Hilbert space  $H_t^y$ . The important result is that every vector  $Y \in H_t^y$  can be represented as

$$Y = \int_0^t \beta(s) dy_s \quad (5)$$

where  $\beta$  is a deterministic square integrable function and the above integral is a stochastic integral. For an account of stochastic integrals see the book of Wong [loc. cit.]. Now using the Projection Theorem, (5), and (F1)-(F3) we can obtain a representation theorem for the estimate  $\hat{z}_t$  as:

$$\hat{z}_t = \int_0^t \left( \frac{\partial}{\partial s} E(z_t v_s') \right) dv_s \quad (6)$$

What we have done so far is quite general. As we have mentioned, Wiener assumed that  $(z_s)$  was a stationary q.m. second-order process, and he obtained a linear integral representation for the estimate where the kernel of the integral operator was obtained as a solution to an integral equation, the Wiener-Hopf equation. As Wiener himself remarked, effective solution to the Wiener-Hopf equation using the method of spectral factorization (see, for example, Youla [6]) could only be obtained when  $(z_s)$  had a rational spectral density. In his fundamental work Kalman ([7, 8, 9]) made this explicit by introducing a Gauss-Markov diffusion model for the signal

$$\begin{cases} dx_t = Fx_t dt + Gd\beta_s \\ z_t = Hx_t \end{cases} \quad (7)$$

where  $x_t$  is an  $n$ -vector-valued Gaussian random process,  $w_t$  is  $m$ -dimensional Brownian motion,  $z_t$  is a  $p$ -vector-valued Gaussian random process, and  $F, G,$  and  $H$  are matrices of appropriate order. We note that (7) is actually an integral equation

$$x_t = x_0 + \int_0^t Fx_s ds + \int_0^t Gd\beta_s \quad (7')$$

where the last integral is a stochastic integral. The Gauss-Markov assumption is no loss of generality since in Wiener’s work the best linear estimate was sought for signals modeled as second-order random processes. The filtering problem now is to compute the best estimate (which is provably linear)

$$\hat{x}_t = P_t(x_t). \quad (8)$$

Moreover, in this new setup no assumption of stationarity is needed. Indeed the matrices  $F, G,$  and  $H$  may depend on time. The derivation of the Kalman filter can now proceed as follows. First note that

$$\hat{x}_t = \int_0^t \frac{\partial}{\partial s} E(x_t v_s') dv_s. \quad (9)$$

(See Equation (6).)

Now we can show that

$$\hat{x}_t - \hat{x}_0 - \int_0^t F\hat{x}_s ds = \int_0^t K(s) dv_s \quad (10)$$

where  $K(s)$  is a square integrable matrix-valued function. This is analogous to the representation theorem given by (5).

Equation (10) can be written in differential form as

$$d\hat{x}_t = F\hat{x}_t dt + K(t) dv_t \quad (11)$$

and let us assume that  $\hat{x}_0 = 0$ . The structure of Equation (11) shows that the Kalman Filter incorporates a model of the signal and a correction term, which is an optimally weighted error =  $K(t)(dy_t - \hat{z}_t dt)$  (see Figure 1).

It remains to find an explicit expression for  $K(t)$ . Here we see an interplay between filtering theory and linear systems theory. The solution of (11) can be written as

$$\hat{x}_t = \int_0^t \Phi(t, s) K(s) dv_s \quad (12)$$

where  $\Phi(t, s)$  is the transition matrix corresponding to  $F$ . From (9) and (12)

$$\Phi(t, s) K(s) = \frac{\partial}{\partial s} E(x_t v_s')$$

and hence

$$K(t) = \frac{\partial}{\partial s} E(x_t v_s')|_{s=t}.$$

Some further calculations using the fact that  $x_t \perp H_s^w$  shows that

$$K(t) = P(t)H',$$

where  $P(t) = E(\tilde{x}_t \tilde{x}_t')$ ,  $\tilde{x}_t = x_t - \hat{x}_t$ . Finally, using the representation of solutions of the linear stochastic differential equations (7) and using (11) we can write a linear stochastic

differential equation for  $\tilde{x}_t$  and write down a representation for  $P(t) = E(\tilde{x}_t \tilde{x}_t')$  as

$$P(t) = \Psi(t, 0)P(0)\Psi'(t, 0) + \int_0^t \Psi(t, s)GG'\Psi'(t, s)ds + \int_0^t \Psi(t, s)P(s)H'HP(s)\Psi'(t, s)ds \quad (13')$$

where  $\Psi(t, s)$  is the transition matrix corresponding to  $(F - PH'H)$ . There is again a role of linear systems theory evident here. Differentiating w.r. to  $t$ , we get a matrix differential equation for  $P(t)$ , the matrix Riccati equation

$$\begin{cases} \frac{dP}{dt} = GG' - P(t)H'HP(t) + FP(t) + P(t)F' \\ P(0) = \text{cov}(x_0) = P_0 \end{cases} \quad (14)$$

Note that  $K(t) = P(t)H'$  is deterministic and does not depend on the observation process  $y$ , and hence can be pre-computed. The approach to the solution of the Wiener Filtering Problem consists in studying the equilibrium behavior of  $P(t)$  as  $t \rightarrow \infty$ . There is again a beautiful interplay between the infinite time behavior of the filter and the structural properties of Equation (7). One can prove that if the pair  $(F, G)$  is stabilizable and  $(H, F)$  is detectable then  $P(t) \rightarrow \bar{P}$  as  $t \rightarrow \infty$  where  $\bar{P}$  is the unique non-negative solution to the algebraic Riccati equation corresponding to (14) and that  $F - \bar{P}H'H$  is a stability matrix. Thus the filter is stable, in the sense that the error covariance converges to the optimal error covariance for the stationary problem even if  $F$  is not a stability matrix. For the linear systems concepts introduced here and the proof of the above results the reader may consult Wonham [10].

### The Linear Quadratic Gaussian (LQG) Problem and the Separation Principle

At about the same time that the theory of filtering using linear stochastic differential equations (Gauss-Markov Processes) was being developed, an analogous development for the optimal control of linear dynamical systems with a quadratic cost function was taking place. This work was inspired by the development of Dynamic Programming by Bellman [11] and the ideas of Caratheodory related to Hamilton-Jacobi Theory [12] and was developed by Merriam [13] and Kalman [14]. For textbook accounts see Brockett [15], Wonham [10], and Bryson and Ho [16]. An extension of the quadratic cost optimal control problem for linear dynamical systems in the presence of additive white process noise perturbations leads us to consider the quadratic cost problem for linear stochastic dynamical systems.

The general situation here is that we are given a linear stochastic dynamical system

$$dx_t = Fx_t dt + Bu_t dt + G d\beta_t \quad (15)$$

and the observation equation

$$dy_t = Hx_t dt + dw_t \quad (16)$$

Here  $(\beta_t)$  and  $(w_t)$  are taken to be independent vector Brownian motions and  $u_t$  is a control variable which needs to be chosen based on the information available to the controller so as to minimize the cost function

$$J(u) = E \left\{ \int_0^T (x_t' Q x_t + u_t' R u_t) dt + x_T' M x_T \right\} \quad (17)$$

where  $Q \geq 0$  is symmetric and  $R > 0$  is symmetric. In the general partial observation case the control  $u_t$  is required to be a function of the past of the observation, i.e., of  $(y_s | 0 \leq s \leq t)$ . Historically, these problems in somewhat specialized situations were first examined and solved by Florentin [17,18], by Joseph [19] in discrete-time, and by Kushner [20]. The definitive treatment of this problem is due to Wonham [21]. See also the important paper of Lindquist [22].

When stochastic disturbances are present, there is a fundamental difference between open-loop control (that is, where the control is not a function of the observations) and feedback control (where control is a function of the past of the observations). In general, feedback control will lead to a lower cost than open-loop control. Furthermore, the only general methodology for handling these problems is Dynamic Programming. To approach the partially observable-stochastic control problem involving linear stochastic dynamics and a quadratic cost function, we first consider the corresponding fully observable stochastic control problem by setting  $w_t \equiv 0, \forall t \in [0, T]$  and  $H \equiv I$ . In this case, the problem can be solved using Dynamic Programming and certain ideas of stochastic calculus which we now describe. We set up the necessary language, which will be useful later.

All stochastic processes will be defined on a fixed probability space  $(\Omega, F, P)$  and a finite time interval  $[0, T]$ , on which there is defined an increasing family of  $\sigma$ -fields  $\{F_t, 0 \leq t \leq T\}$ . It is assumed that each process  $\{x_t\}$  is adapted to  $F_t$ —i.e.,  $x_t$  is  $F_t$ -measurable for all  $t$ . The  $\sigma$ -field generated by  $\{x_s, 0 \leq s \leq t\}$  is denoted by  $F_t^x = \sigma\{x_s, 0 \leq s \leq t\}$ .  $(x_t, F_t)$  is a *martingale* if it is a *supermartingale* and a *sub-martingale*.  $E[x_t | F_s] = x_s, x_t$  is a *supermartingale* if  $E[x_t | F_s] \leq x_s$  and a *submartingale* if  $E[x_t | F_s] \geq x_s$ . The process  $(x_t, F_t)$  is a *semimartingale* if it has a decomposition  $x_t = x_0 + a_t + m_t$ , where  $(m_t, F_t)$  is a martingale and  $\{a_t\}$  is a process of bounded variation. Given two square integrable martingales  $(m_t, F_t)$  and  $(n_t, F_t)$ , one can define the *predictable quadratic covariation*  $\langle m, n \rangle_t, F_t$  to be the unique “predictable process of integrable variation” such that  $(m_t n_t - \langle m, n \rangle_t, F_t)$  is a martingale. For the purposes of this article, however, the only necessary facts concerning  $\langle m, n \rangle$  are that (a)  $\langle m, n \rangle_t = 0$  if  $m_t, n_t$  is a martingale; and (b) if  $\beta$  is a standard Brownian motion process, then

$$\langle \beta, \beta \rangle_t = t \quad \text{and} \quad \left\langle \int_0^t \eta_s^1 d\beta_s, \int_0^t \eta_s^2 d\beta_s \right\rangle_t = \int_0^t \eta_s^1 \eta_s^2 ds.$$

Finally, we need to use the Ito differential rule. Suppose that  $x_t$  is a vector diffusion process given by

$$x_t = x_0 + \int_0^t f(x_s) ds + \int_0^t G(x_s) d\beta_s \quad (18)$$

where  $x_t \in \mathbf{R}^n$ ,  $\beta_t \in \mathbf{R}^m$  is a vector of independent Brownian motions and  $f$  and  $g$  are vector and matrix-valued functions, suitably smooth.

In the above the last integral is a stochastic integral which is a generalization of the Wiener integral we have encountered before and is defined through an appropriate approximation process and a quadratic mean-limiting process (see, for example, Wong [5]). This cannot be defined as a Lebesgue-Stieltjes integral because the trajectories of Brownian motion are not of bounded variation almost surely. Now, if  $\psi$  is a twice continuously differentiable function of  $x$ , then

$$\begin{aligned} \psi(x_t) &= \psi(x_0) + \sum_{i=1}^n \int_0^t \frac{\partial \psi}{\partial x^i}(x_s) dx_s \\ &\quad + \frac{1}{2} \sum_{i,j=1}^n \int_0^t \frac{\partial^2 \psi}{\partial x^i \partial x^j}(x_s) a^{ij}(x_s) ds \end{aligned} \quad (19)$$

where  $A(x) = (a^{ij}(x))_{i,j=1}^n = G(x)G'(x)$ .

Note that in contrast to ordinary calculus we have a second-order term in the formula arising from the variance properties of Brownian motion. This is the Ito differential rule.

Let us now return to the fully observable stochastic control problem. Associated with the linear stochastic differential equation

$$\begin{cases} dx_s = Fx_s ds + Gd\beta_s & s \in [t, T] \\ x_t = x(\text{fixed}) \end{cases} \quad (20)$$

and  $L$  is the operator

$$(Lf)(t, x) = f_t + f'_x Fx + \frac{1}{2} \text{tr}(G'f_{xx}G)$$

Then an application of Ito's differential rule shows that for  $V$  smooth

$$V(t, x) = -E_{t,x} \left[ \int_t^T LV(s, x_s) ds - x'_T M x_T \right] \quad (21)$$

(Dynkin's formula).

This formula is valid in a much more general context. Now returning to the control problem let us consider admissible controls (feedback) in the class

$$u(t, x_t) = K(t)x_t \quad (22)$$

where  $K(t)$  is a piecewise continuous matrix-valued function. This is quite a general class of control laws, and it can be shown that there is nothing to be gained by considering more general linear non-anticipative control laws. Consider an optimal control  $u_t^0 = K_0(t)x_t$ . Then

$$\begin{aligned} V^0(t, x) &= E_{t,x} \left[ \int_t^T (x_s^{0'} Q x_s^0 + u_s^{0'} R u_s^0) ds + x_T^{0'} M x_T^0 \right] \\ &= E_{t,x} \left[ \int_t^T x_s^{0'} S^0(t) x_s^0 ds + x_T^{0'} M x_T^0 \right] \end{aligned}$$

where  $x_s^0$  is the solution of

$$\begin{cases} dx_s = (F + BK_0(t))x_s + Gd\beta_s \\ x_t = x, \\ S^0(t) = S_{K_0}(t) = Q + K_0'(t)RK_0 \end{cases}$$

For a feedback matrix  $K(t)$ , let

$$(L_K f)(t, x) = f_t + f'_x (F + BK(t))x + \frac{1}{2} \text{tr}(G'f_{xx}G)$$

and let  $S_K(t) = Q + K(t)RK(t)$ .

Then applying Bellman's Principle of Optimality we obtain

$$0 = L_{K_0} V^0(t, x) + x' S_{K_0} x \leq L_K V^0(t, x) + x' S_K x, \quad (23)$$

where  $K_0$  is the optimal feedback gain and  $K$  is any admissible feedback gain. The above equation can be explicitly written as

$$\min_K \left( \begin{aligned} &V_t + \frac{1}{2} \text{tr}(G'V_{xx}G) + V_x(F - BK(t))x \\ &\quad + x'(Q + K'(t)RK(t))x \end{aligned} \right) = 0. \quad (24)$$

Note that in contrast to the deterministic situation ( $\beta \equiv 0$ ), there is a second-order operator in the above equation. This equation can be solved for  $K_0$ ,  $V_0$  using essentially the same method as in the deterministic case. The result is that the optimal control  $u^0(t)$  is given by

$$u^0(t) = -R^{-1}B'P(t)x_t$$

where  $P(t)$  is a symmetric non-negative solution of the matrix Riccati equation

$$\begin{cases} \frac{dS}{dt} + S(t)F + F'S(t) + Q - S(t)BR^{-1}B'S(t) = 0 \\ S(T) = M \end{cases} \quad (25)$$

and the optimal cost function is

$$J(u_0) = \int_0^T \text{tr}(G'P(s)G) ds + m_0' P(0) m_0 + \text{tr}(\Sigma_0 P(0)) \quad (26)$$

where  $E(x_0) = m_0$  and  $\text{cov}(x_0) = \Sigma_0$ .

It is interesting to note that the optimal control is the same as in the deterministic case, but not the expression for the optimal cost function. Indeed the deterministic situation can be recovered by setting  $C = 0$  and  $P\Sigma_0 = 0$ . This result, however, crucially depends on the quadratic nature of the cost functions and the linearity of the dynamics.

In proving optimality we have restricted ourselves to control laws which are linear. One can prove the same results by considering non-linear control laws which are Lipschitz function of  $x$  (see Wonham, *loc. cit.*).

Let us now return to the partially observable problem. The key idea here is to introduce the idea of an information state (cf. Davis and Varaiya [23]) and reduce the partially observable problem to the fully observable problem. Now the information state is the conditional distribution

$P^u(x_t | y_s, 0 \leq s \leq t)$  where the superscript denotes the dependence on the control  $u$ . In our case this conditional distribution is conditionally Gaussian and given by the Kalman filter

$$d\hat{x}_t = F\hat{x}_t dt + K(t)dv_t + B(t)u_t \quad (27)$$

where  $K(t)$  is given by (13). Furthermore, the innovations process  $v_t$  as given by (4) satisfies (F1), (F2), and (F3) even in this case. In fact  $v_t$  is a Brownian motion adapted to  $F_t^y$ , the  $\sigma$ -field generated by  $(y_s | 0 \leq s \leq t)$ . This is true for control laws which are Lipschitz functions of the past of  $y$ . If we restrict ourselves to this class, then Wonham showed that the admissible control laws are  $u_t = \varphi(\hat{x}_t)$  where  $\varphi$  is Lipschitz. The issue of the choice of admissible control laws is a subtle one because of questions of existence and uniqueness of non-linear stochastic differential equations. For a detailed discussion cf. Lindquist [*loc. cit.*]. Now by writing  $x_t = \hat{x}_t + \tilde{x}_t$ , where  $\tilde{x}_t$  is the error process and using the fact that  $\tilde{x}_t \perp H_t^{y,u}$ , the cost function given by (17) can be rewritten as:

$$J(u) = E \left[ \int_0^T (\dot{\hat{x}}_t' Q \dot{\hat{x}}_t + u_t' R u_t) dt + \hat{x}_T' M \hat{x}_T \right] + \int_0^T \text{Tr}[P(t)Q] dt + \text{Tr}(P(T)M). \quad (28)$$

Now it can be shown using the arguments of the fully observable case that the optimal control is given by

$$u^0(t) = -R^{-1}B'(t)\Lambda(t)\hat{x}_t \quad (29)$$

where  $\Lambda(t)$  is a symmetric non-negative solution of Equation (25) and  $\hat{x}_t$  is given by (27). Now  $\Lambda(t)$  is the same as in the deterministic optimal control problem, and we have the separation theorem which states that the partially observable stochastic control separates into the solution of a deterministic optimal control problem and a Kalman filtering problem.

We do not go into a detailed discussion of the relationship between the separation principle and the certainty equivalence principle here (cf. Witsenhausen, [24]). It should be mentioned that the certainty equivalence principle was discussed in the economics literature in the late '50s (cf. Holt et al. [25]). For an illuminating discussion on the distinctions between open-loop stochastic control, feedback control, and open-loop feedback control, see Dreyfus [26].

### Nonlinear Filtering

To develop the theory of non-linear filtering we follow the scheme of development of linear filtering theory. It is interesting that using the theory of martingales the generalization to the non-linear filtering case is very natural. The ideas that we use were first introduced and developed by Frost-Kailath [27] and in somewhat definitive form by Fujisaki-Kallianpur-Kunita [28]. The historical development proceeded in a somewhat different manner and we shall discuss this in a later part of this section.

Our basic model is the observation equation

$$y_t = \int_0^t z_s ds + w_t \quad (30)$$

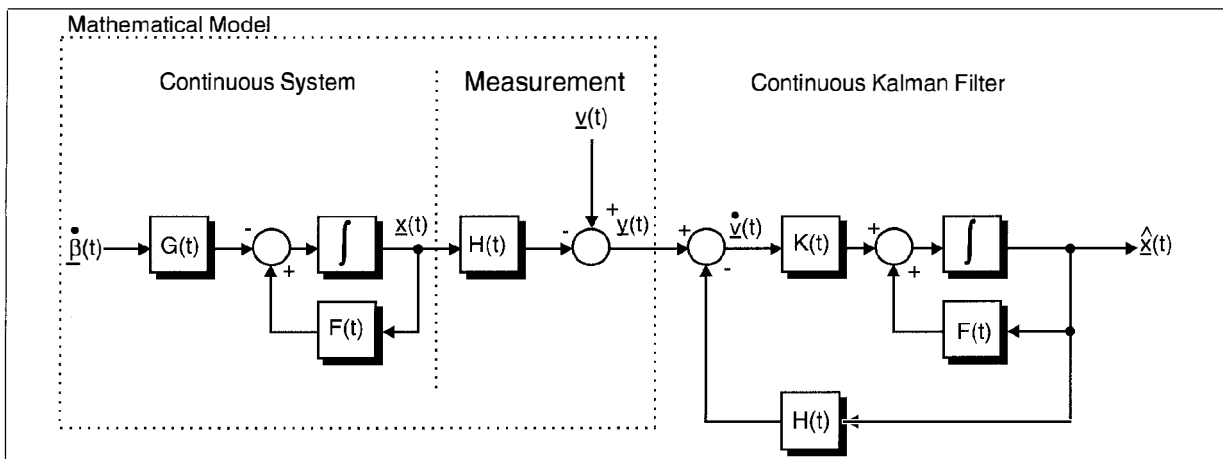


Fig. 1. System model and continuous Kalman filter.

with the assumptions

(H1)  $y_t$  is real-valued process

(H2)  $w_t$  is standard Brownian motion

(H3)  $E \left[ \int_0^T z_s^2 ds \right] < \infty$

(H4)  $(z_t)$  is independent of  $w_t$ .

These assumptions are similar to (A1), (A2), (A3)' in the linear situation.

Consider the innovations process

$$\left. \begin{aligned} v_t &= y_t - \int_0^t \hat{z}_s ds \\ \text{where } \hat{z}^s &= E(z_s | F_s^y) \end{aligned} \right\} \quad (31)$$

It can now be shown that:

The process  $(v_t, F_t^y)$  is standard Brownian motion and  $F_s^y$  and  $\sigma(v^u - v_t | 0 \leq s \leq t < u \leq T)$  are independent. This result is proved by showing that  $v_t$  is a square integrable martingale with continuous sample paths with quadratic variation  $t$ , and the result follows from the Levy characterization of Brownian motion.

Now analogous to (F3) in the linear case one can prove that

$$F_t^y = \mathcal{F}_t^v; \quad (32)$$

that is, the innovations contains the same information as the observation. This rather delicate result was proved by Allinger-Mitter [29].

Now combining this with the representation of square integrable martingales as stochastic integrals due to Kunita and Watanabe, we obtain the following:

Every square-integrable martingale  $(m_t, F_t^y)$  can be represented as

$$m_t = E(m_0) + \int_0^t \eta_s ds \quad (33)$$

$$\int_0^T E(\eta_s^2) ds < \infty \text{ and } \eta_t \text{ is adapted to } F_t^y.$$

It should be remarked that Fujisaki-Kallianpur-Kunita in their important paper proved the same result without (32) holding but with  $\eta_t$  adapted to  $F_t^y$ .

To proceed further let us assume that

$$z_t = h(x_t) \quad (34)$$

and  $x_t$  satisfies a stochastic differential equation

$$x_t = x_0 + \int_0^t f(x_s) ds + \int_0^t G(x_s) d\beta_s,$$

which is the same as Equation (18).

Suppose we want to obtain the estimate

$$\pi_t(\varphi) \stackrel{\Delta}{=} E(\varphi(x_t) | F_t^y). \quad (35)$$

We want to obtain a recursive equation for  $\pi_t(\varphi)$ . We need some preliminaries.

Let  $L$  be the second-order elliptic operator defined by

$$L\psi = \sum_{i=1}^n f^i(x) \frac{\partial^i \psi}{\partial x^i} + \sum_{i,j=1}^n a^{ij}(x) \frac{\partial^2 \psi}{\partial x^i \partial x^j} \quad (36)$$

$$\text{and } A(x) = (a^{ij}(x))_{i,j=1}^n = G(x)G'(x).$$

Then we can write Ito's differential rule (19) as:

$$\psi(x_t) - \psi(x_0) - \int_0^t L\psi(x_s) ds = \int_0^t (\nabla \psi(x_s))' G(x_s) d\beta_s \quad (37)$$

where  $\nabla$  is the gradient operator, and the last term

$M_t^y = \int_0^t (\nabla \psi(x_s)) G(x_s) d\beta_s$  is a  $F_t^y$ -martingale (being a stochastic integral).

To obtain the recursive equation for  $\pi_t(\varphi)$ , one shows that

$M_t^\varphi = \pi_t(\varphi) - \pi_0(\varphi) - \int_0^t \pi_s(L\varphi) ds$  is a square integrable  $F_t^y$ , hence

$F_t^y$  martingale. Therefore from the representation theorem

$M_t^\varphi = \int_0^t \eta_s d\nu_s$ , where  $\eta_s$  is square integrable and adapted to  $F_t^y$ . Therefore

$$\pi_t(\varphi) = \pi_0(\varphi) + \int_0^t \pi_s(L\varphi) ds + \int_0^t \eta_s d\nu_s. \quad (38)$$

It remains to identify  $\eta_s$ . This can be obtained as follows:

By the Ito differential rule (37)

$$\varphi(x_t) = \varphi(x_0) + \int_0^t L\varphi(x_s) ds + M_t^\varphi.$$

Also

$$y_t = y_0 + \int_0^t h(x_s) ds + w_t.$$

Now, using the Ito-differential rule for semi-martingales,

$$\begin{aligned} \varphi(x_t) y_t &= \varphi(x_0) y_0 + \int_0^t y_s d\varphi(x_s) + \int_0^t \varphi(x_s) dy_s + \langle M^\varphi, w \rangle_t \\ &= \varphi(x_0) y_0 + \int_0^t y_s (L\varphi(x_s) ds + dM_s^\varphi) \\ &\quad + \int_0^t \varphi(x_s) (h(x_s) ds + dw_s) \end{aligned} \quad (39)$$

(since  $\langle M^\varphi, w \rangle_t = 0$  from the independence of  $(x_t)$  and  $(w_t)$ .  
From the innovations representation

$$y_t = y_0 + \int_0^t \pi_s(h) ds + v_t. \quad (40)$$

Therefore

$$\begin{aligned} \pi_t(\varphi) y_t &= \pi_\bullet(\varphi) y_\bullet + \int_0^t \pi_s(\varphi) (\pi_s(h) ds + dv_s) \\ &+ \int_0^t y_s (\pi_s(L\varphi) ds + \eta_s dv_s) - \langle N, v \rangle_t \\ &\text{where } N_t = \int_0^t \eta_s dv_s \\ &= \pi_\bullet(\varphi) y_0 + \int_0^t \pi_s(\varphi) (\pi_s(h) ds + dv_s) \\ &+ \int_0^t y_s (\pi_s(L\varphi) ds + \eta_s dv_s) + \int_0^t \eta_s ds. \end{aligned} \quad (41)$$

Now noting that

$$E(\varphi(x_t) y_t - \pi_t(\varphi) y_t | \mathcal{F}_t^y) = 0,$$

from (40) and (41) we get

$$\eta_t = \pi_t(h\varphi) - \pi_t(\varphi)\pi_t(h)$$

and hence we get from (38):

$$\pi_t(\varphi) = \pi_0(\varphi) + \int_0^t \pi_s(L\varphi) ds + \int_0^t (\pi_s(h\varphi) - \pi_s(h)\pi_s(\varphi)) dv_s. \quad (42)$$

This is one of the fundamental equations of non-linear filtering. If the conditional distribution  $\pi_t$  has a density given by  $\tilde{p}(t, x)$ , then  $\tilde{p}$  satisfies the stochastic partial differential equation

$$d\tilde{p}(t, x) = L^* \tilde{p}(t, x) dt + \tilde{p}(t, x) [h(x) - \pi_t(h)] dv_t \quad (43)$$

where  $\pi_t(h) = \int h(x) \tilde{p}(t, x) dx$ . The question of existence of a conditional density can be discussed using the Malliavin calculus [46]. Equation (43) in this form, where the Ito calculus is involved, was first derived by Kushner [30]. The difficulty in deriving a solution for a conditional statistic  $\hat{x}_t \stackrel{\Delta}{=} \pi_t(x) = \int x \tilde{p}(t, x) dx$  is the so-called closure problem. The equation is

$$d\hat{x}_t - \pi_t(f) dt + (\pi_t(hx) - \pi_t(h)\hat{x}_t) dv_t. \quad (44)$$

Note that computation of  $\hat{x}_t$  requires computing

$$\pi_t(f) = \int f(x) \tilde{p}(t, x) dx, \quad \pi_t(hx) = \int h(x) x \tilde{p}(t, x) dx$$

and  $\pi_t(h) \stackrel{\Delta}{=} \int h(x) \tilde{p}(t, x)$ , and this requires solving stochastic differential equations for each of these above quantities, which in their turn involve higher moments. Hence non-linear filters are almost always infinite-dimensional. There are only a few known examples where the filter is known to be finite-dimensional. The first is the linear-gaussian situation leading to the Kalman filter which we have treated in an earlier section. The second is the finite-state case, first considered in an important paper by Wonham [31]. Let  $x_t$  be a finite-state Markov process taking values  $S = (s_1, \dots, s_N)$ . Let  $p_t = (p_t^1, \dots, p_t^N)$  be the probability vector where  $p_t^i = \text{Prob}(x_t = s_i)$ . Then the evolution of  $p_t$  is given by the forward Kolmogoroff equation

$$\frac{dp_t}{dt} = A p_t.$$

If we denote by  $\tilde{p}_t = \text{Prob}(x_t = s_i | \mathcal{F}_t^y)$

$$B = \text{diag}(h(s_1), \dots, h(s_N)) \quad \text{and} \quad b' = (h(s_1), \dots, h(s_N)),$$

then  $\tilde{p}_t$  satisfies

$$d\tilde{p}_t = A \tilde{p}_t dt + [B - (b' \tilde{p}_t) I] \tilde{p}_t (dy_t - (b' \tilde{p}_t) dt). \quad (45)$$

We shall discuss a further example leading to a finite-dimensional filter a little later. One of the difficulties with Equation (43) is that it is a non-linear stochastic partial differential equation. An important idea due to Zakai [32], Duncan [33], and Mortensen [34] is to write  $\pi_t(\varphi)$  as

$$\pi_t(\varphi) = \frac{\rho_t(\varphi)}{\rho_t(1)} \quad (46)$$

where  $\rho_t(\varphi)$  satisfies

$$\rho_t(\varphi) = \rho_0(\varphi) + \int_0^t \rho_s(L\varphi) ds + \int_0^t \rho_s(h\varphi) dy_s \quad (47)$$

$\rho_t$  is an un-normalized version of  $\pi_t$ . Note that this is a linear stochastic partial differential equation. This is intimately related to the Feynman-Kac formula for integrating linear parabolic equations with a potential term. For a discussion between the analogies between non-linear filtering and quantum mechanics see Mitter [35]. Recall that the original probability space is  $(\Omega, \mathcal{F}, P)$  on which there is an increasing family of  $\sigma$ -fields  $(\mathcal{F}_t)_{t \geq 0}$  and the process  $(x_t)$  is adapted to it. Define a new probability measure  $P_0$  on  $(\Omega, \mathcal{F})$  in terms of the Radon-Nikodym derivative

$$\begin{aligned} \frac{dP_0}{dP} &= \exp\left(-\int_0^T h(x_s) dy_s - \frac{1}{2} \int_0^T h^2(x_s) ds\right) \\ &\stackrel{\Delta}{=} \Lambda_T. \end{aligned} \quad (48)$$

Under  $P_\bullet$ ,  $(y_t)$  is standard Brownian motion,  $(x_t)$  and  $(y_t)$  are independent, and  $(x_t)$  has the same distribution under  $P_0$  and  $P$ . Now,

$$\begin{aligned} \pi_t(\phi)E(\phi(x_t)|\mathcal{F}_t^y) &= \frac{E_0(\phi(x_t)\Lambda_t|\mathcal{F}_t^y)}{E_0(\Lambda_t|\mathcal{F}_t^y)} \\ &\stackrel{\Delta}{=} \frac{\rho_t(\phi)}{\rho_t(1)}. \end{aligned} \quad (49)$$

Furthermore, we can prove that

$$\tilde{\Lambda}_t \stackrel{\Delta}{=} E_0(\Lambda_t|\mathcal{F}_t^y) = \exp\left(\int_0^t \pi_s(h)dy_s - \frac{1}{2}\int_0^t \pi_s(h)^2 dy_s\right).$$

From (49)  $\rho_t(\phi) = \pi_t(\phi)\tilde{\Lambda}_t$ . Then using the Ito differential rule we get Equation (47). This derivation is due to Davis and Marcus [36], where the full details can be found. The measure transformation idea in stochastic differential equation is due to Girsanov (cf. Liptser and Shirayev [37] and the references cited there).

Equation (47) is an Ito stochastic partial differential equation. There is a calculus, the so-called Stratanovich calculus, which in many ways is like ordinary calculus. The conditional density equation for non-linear filtering was derived using this calculus by Stratanovich [38]. For the relation between the two calculi see Wong [5]. This is an important modeling question. The Stratanovich form of Equation (47) is

$$\rho_t(\phi) = \rho_0(\phi) + \int_0^t \rho_s \left( L\phi - \frac{1}{2}h^2\phi \right) ds + \int_0^t \rho_s(h\phi) \circ dy_s \quad (50)$$

where the last integral is a (symmetric) Stratanovich integral. It should be noted that geometry is preserved when we work with the Stratanovich form of the equation. The relation between (47) and (50) involves the Wong-Zakai correction (note that the generator  $L$  in Equation (50) has been replaced by  $L - \frac{1}{2}h^2$ ). If

$\rho_t$  has a density  $q(t, x)$  then  $q(t, x)$  satisfies a linear stochastic partial differential equation

$$dq(t, x) = \left( L^* - \frac{1}{2}h^2 \right) q(t, x) + h(x)q(t, x) \circ dy_t \quad (51)$$

It turns out that the Lie algebra generated by the operators  $L^* - \frac{1}{2}h^2$  and  $h$  plays a role in the existence of a finite-dimensional filter. For a discussion of this see Brockett [39] and Mitter [40]. An example where a finite-dimensional filter exists is the following:

$$\begin{cases} dx_t = f(x_t)dt + \beta_t, & x_t \in \mathbf{R} \\ dy_t = x_t dt + dw_t \end{cases}$$

and  $f$  satisfies the Riccati equation

$$\frac{df}{dx} + f^2 = x^2$$

This example, first considered by Benes [41], is intimately related to the Kalman filter using a Gauge transformation  $q(t, x) \mapsto \psi(x)q(t, x)$  where  $\psi$  is invertible (cf. Mitter, loc. cit.). On the other hand it can be shown that for the filtering problem

$$\begin{aligned} x_t &= \beta_t \\ dy_t &= x_t^3 dt + dw_t \end{aligned}$$

no finite-dimensional filter exists [42].

There are a number of other issues in non-linear filtering which we do not consider in this article. For discussions of pathwise non-linear filtering where the filter depends continuously on  $y$  see Clark [43] and Davis [44]. For the important problem of obtaining lower bounds on the mean-squared error see Bobrovsky-Zakai [45]. Results can be obtained when the signal  $(z_t)$  and the noise are correlated (cf. the review paper by Pardoux [46]).

### Optimal Stochastic Control (Fully Observable Case)

The theory of optimal stochastic control in the fully observable case is quite similar to the theory we have sketched in the third section above, in connection with the linear quadratic stochastic control problem. The conceptual ideas here originated in the Dynamic Programming methodology developed by Bellman. An early work here is that of Howard [47], though not in the continuous-state continuous-time formulation. Important early papers related to this section are those of Florentin [17] and Fleming [48]. Many other people, notably Kushner, have contributed to this subject. For a textbook presentation where other references can be found, see Fleming-Rishel [49].

Consider the problem of minimizing

$$J(t, x, u) = E_{tx} \left[ \int_t^T l(x(s), u(s)) ds + \psi(x(T)) \right] \quad (52)$$

where  $x_s \in \mathbf{R}^n$  evolves according to the stochastic differential equation

$$\begin{cases} dx_s = f(x_s, u_s) ds + G(x_s, u_s) d\beta_s \\ x_t = x \end{cases} \quad (53)$$

We define the value function  $V(t, x)$  as:

$$V(t, x) = \inf_{u \in U} J(t, x, u) \quad (54)$$

By Bellman's Principle of Optimality,

$$V(t, x) = \inf_{u \in U} E_{tx} \left[ \int_t^{t+h} l(x_s, u_s) ds + V(t+h, x_{t+h}) \right] \quad (55)$$

$$t \leq t+h \leq T_1$$



Now, if we take constant controls  $v$  on the interval  $[t, t + h]$ , we clearly have

$$V(t, x) \leq E_{tx} \int_t^{t+h} \ell(x_s, v) ds + E_{tx} V(t+h, x_{t+h}) \quad (56)$$

Now by Dynkin's formula (Ito Differential Rule)

$$E_{tx} [V(t+h, x_{t+h}) - V(t, x)] = E_{tx} \int_t^{t+h} (V_s(s, x_s) + L^v V(s, x_s)) ds.$$

Dividing both sides by  $h$  and taking the limit as  $h \rightarrow 0$ , we obtain,  $\forall v$

$$V_t(t, x) + L^v V(t, x) + \ell(x, v) \geq 0. \quad (57)$$

Now, if the class of admissible controls are taken to be Markov in the sense

$$u_s = g(s, x_s) \quad (58)$$

with  $g$  Lipschitz say, and

$$u_s^* = g^*(s, x_s)$$

is an optimal Markov control we get

$$V_t(t, x) + L^{g^*} V(t, x) + \ell(x, g^*(t, x)) = 0.$$

Therefore from (57) and (58) we get the fundamental Dynamic Programming equation

$$\min_v [V_t(t, x) + L^v V(t, x) + \ell(x, v)] = 0, \quad V(t, x) = \psi(x). \quad (60)$$

An optimal Markov control policy  $g^*$  is obtained by carrying out the minimization above pointwise. A solution  $W(t, x)$  (classical) of the above equation allows one to verify that  $W$  is a value function.

Other than the linear quadratic problem discussed in the third section of this article, few explicit solutions of this equation are known. For controlled Markov processes with a finite state space equations (59) reduces to a non-linear system of ordinary differential equations.

### Optimal Stochastic Control (Partially Observable Case)

We consider the following partially observable stochastic control problem

$$\begin{cases} dx_t = f(x_t, u_t) dt + G(x_t) d\beta_t \\ dy_t = h(x_t) dt + dw_t \end{cases} \quad (61)$$

and we are required to minimize

$$J(t, x) = E_{tx} \left[ \int_t^T L(x_s, u_s) ds + \psi(x_T) \right]. \quad (62)$$

The controls  $u$  are required to be suitable functions of the past of  $y$ .

The conceptual idea to discuss this problem is similar to that used for the LQG problem. But there are severe technical difficulties which we ignore in this presentation. First we introduce the information state for this problem. For this purpose define the operator (see Equation (36))

$$L^u \phi = \sum_{i=1}^n f^i(x, u) \frac{\partial^i \phi}{\partial x^i} + \sum_{i,j} a^{ij}(x) \frac{\partial^2 \phi}{\partial x^i \partial x^j}. \quad (63)$$

Then the information state is given by (see Equation (51))

$$d q^u(t, x) = (L^{u^*})^* q^u(t, x) dt + h(x) q^u(t, x) dy_t. \quad (64)$$

Note that  $q^u(t, x)$  is the unnormalized conditional density corresponding to the non-linear filtering problem for (60).

The idea now is to rewrite the cost function given by (61) in terms of the information state  $q^u(t, x)$ . Formally this can be done and the resulting expression is

$$J(t, x) = E_{tx} \left[ \int_t^T \int L(x, u) q^u(t, x) dx + \int \psi(x) q^u(t, x) dx \right]. \quad (65)$$

Equations (64) and (65) constitute the equivalent fully observable stochastic control problem. Note that the problem is essentially infinite-dimensional since the information state is infinite-dimensional. In principle we could write Dynamic Programming conditions for this problem, but other than the linear quadratic gaussian situation and the case of risk-sensitive control where the cost function is an exponential of a quadratic function (cf. Whittle [50], Bensoussan-Van Schuppen [51]), no explicit solution for these problems are known.

The partially observable stochastic control problem was probably first treated by Florentin [18]. There is important work here by Davis and Varaiya [52] and Fleming and Pardoux [53]. For detailed discussions see the research monograph by Borkar [54] and the references cited there.

### Applications

The linear quadratic gaussian methodology has found wide applications in aerospace systems. It is also used as a design tool for the design of multi-variable control systems. The principal application of optimal non-linear stochastic control seems to be in the domain of finance. For these applications see the important book of Merton [55].

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