New Results in Linear Filtering and Prediction Theory

A nonlinear differential equation of the Riccati type is derived for the covariance matrix of the optimal filtering error. The solution of this "variance equation" completely specifies the optimal filter for either finite or infinite smoothing intervals and stationary or nonstationary statistics.

The variance equation is closely related to the Hamiltonian (canonical) differential equations of the calculus of variations. Analytic solutions are available in some cases. The significance of the variance equation is illustrated by examples which duplicate, simplify, or extend earlier results in this field.

The Duality Principle relating stochastic estimation and deterministic control problems plays an important role in the proof of theoretical results. In several examples, the estimation problem and its dual are discussed side-by-side.

Properties of the variance equation are of great interest in the theory of adaptive systems. Some aspects of this are considered briefly.

1 Introduction

At present, a nonspecialist might well regard the Wiener-Kolmogorov theory of filtering and prediction [1, 2] as classical—in short, a field where the techniques are well established and only minor improvements and generalizations can be expected.

That this is not really so can be seen convincingly from recent results of Shinbrot [3], Steeg [4], Pugachev [5, 6], and Parzen [7]. Using a variety of time-domain methods, these investigators have solved some long-standing problems in nonstationary filtering and prediction theory. We present here a unified account of our own independent researches during the past two years (which overlap with much of the work [3-7] just mentioned), as well as numerous new results. We, too, use time-domain methods, and obtain major improvements and generalizations of the conventional Wiener theory. In particular, our methods apply without modification to multivariate problems.

The following is the historical background of this paper.

In an extension of the standard Wiener filtering problem, Pollin [8] obtained relationships between time-varying gains and error variances for a given circuit configuration. Later, Hanson [9] proved that Pollin's circuit configuration was actually optimal for the assumed statistics; moreover, he showed that the differential equations for the error variance (first obtained by Pollin) follow rigorously from the Wiener-Hopf equation. These results were then generalized by Buzy [10], who found explicit relationships between the optimal weighting functions and the error variances; he also gave a rigorous derivation of the variance equations and those of the optimal filter for a wide class of nonstationary signal and noise statistics.

Independently of the work just mentioned, Kalman [11] gave a new approach to the standard filtering and prediction problem. The novelty consisted in combining two well-known ideas:

(i) the "state-transition" method of describing dynamical systems [12-14], and

(ii) linear filtering regarded as orthogonal projection in Hilbert space [15, pp. 150-155].

As an important by-product, this approach yielded the Duality Principle [11, 16] which provides a link between (stochastic) filtering theory and (deterministic) control theory. Because of the duality, results on the optimal design of linear control systems [13, 16, 17] are directly applicable to the Wiener problem. Duality plays an important role in this paper also.

When the authors became aware of each other's work, it was soon realized that the principal conclusion of both investigations was identical, in spite of the difference in methods:

Rather than to attack the Wiener-Hopf integral equation directly, it is better to convert it into a nonlinear differential equation, whose solution yields the covariance matrix of the minimum filtering error, which in turn contains all necessary information for the design of the optimal filter.

2 Summary of Results: Description

The problem considered in this paper is stated precisely in Section 4. There are two main assumptions:

(A1) A sufficiently accurate model of the message process is given by a linear (possibly time-varying) dynamical system excited by white noise.

(A2) Every observed signal contains an additive white noise component.

Assumption (A2) is unnecessary when the random processes in question are sampled (discrete-time parameter); see [11]. Even in the continuous-time case, (A2) is no real restriction since it can be removed in various ways as will be shown in a future paper. Assumption (A1), however, is quite basic; it is analogous to but somewhat less restrictive than the assumption of rational spectra in the conventional theory.

Within these assumptions, we seek the best linear estimate of the message based on past data lying in either a finite or infinite time-interval.

The fundamental relations of our new approach consist of five equations:
First we define a dynamical system which is the dual (or adjoint) of (1). Let

\[
\begin{align*}
    \mathbf{x}(t) &= \mathbf{F}(t) \mathbf{x}(t) + \mathbf{G}(t) \mathbf{u}(t) \\
    \mathbf{H}(t) &= \mathbf{H}(t)
\end{align*}
\]  

(16)

Let \( \Phi^*(t, t_0) \) be the transition matrix of the dual dynamical system of (1):

\[
    d\mathbf{x}^*(t)/dt = \mathbf{F}^*(t)\mathbf{x}^*(t) + \mathbf{G}^*(t)\mathbf{u}^*(t)
\]  

(17)

It is easy to verify the fundamental relation

\[
    \Phi^*(t, t_0) = \Phi(t, t)
\]  

(18)

With these notation conventions, we can now state the optimal regulator problem. Consider the linear dynamical system (17). Find a "control law"

\[
    \mathbf{u}^*(t) = \mathbf{k}^*(\mathbf{x}^*(t), \mathbf{u}^*(t))
\]  

(19)

with the property that, for this choice of \( \mathbf{u}^*(t) \), the "performance index"

\[
    J(\mathbf{x}^*, t^*, t_0; \mathbf{u}^*) = \|\mathbf{k}^*(\mathbf{x}^*, t); \mathbf{u}^*\|_p + \int_{t_0}^{t^*} \|\mathbf{x}^*(\tau^*); \mathbf{u}^*(\tau^*)\|_{Q(\tau^*)} + \|\mathbf{u}^*(\tau^*)\|_{R(\tau^*)} d\tau^*
\]  

(20)

assumes its greatest lower bound.

This is a natural generalization of the well-known problem of the optimization of a regulator with integrated-squared-error type of performance index.

The mathematical theory of the optimal regulator problem has been explored in considerable detail [17]. These results can be applied directly to the optimal estimation problem because of the duality theorem. The solutions of the optimal estimation problem and of the optimal regulator problem are equivalent under the duality relations (16).

The nature of these solutions will be discussed in the sequel. Here we pause only to observe a trivial point: By (14), the solutions of the estimation problem are necessarily linear; hence the same must be true if the duality theorem is correct of the solutions of the optimal regulator problem, in other words, the optimal control law \( \mathbf{k}^* \) must be a linear function of \( \mathbf{x}^* \).

The first proof of the duality theorem appeared in [11], and consisted of comparing the end results of the solutions of the two problems. Assuming only that the solutions of both problems result in linear dynamical systems, the proof becomes much simpler and less mysterious; this argument was carried out in detail in [16].

Remark (f) If we generalize the optimal regulator problem to the extent of replacing the first integrand in (20) by

\[
    \|\mathbf{y}^*(\tau^*) - \mathbf{y}_0^*(\tau^*)\|_{Q(\tau^*)}
\]

where \( \mathbf{y}_0^*(\tau^*) \equiv 0 \) is the desired output (in other words, if the regulator problem is replaced by a servomechanism or follow-up problem), then we have the dual of the estimation problem with \( \mathbf{w}(t) \equiv 0 \).

6 Examples: Problem Statement

To illustrate the matrix formalism and the general problems stated in Sections 4–5, we present here some specific problems in the standard block-diagram terminology. The solution of these problems is given in Section 11.

Example 1. Let the model of the message process be a first-order, linear, constant-dynamical system. It is not assumed that the model is stable; but if so, this is the simplest problem in the Wiener theory which was discussed first by Wiener himself [1, pp. 91–92].

Fig. 1 Example 1: Block diagram of message process and optimal filter

The model of the message process is shown in Fig. 1(a). The various matrices involved are all defined by \( 1 \times 1 \) and are

\[
    \mathbf{F}(t) = [f_1], \quad \mathbf{G}(t) = [1], \quad \mathbf{H}(t) = [1],
\]

\[
    \mathbf{Q}(t) = [q_1], \quad \mathbf{R}(t) = [r_1]
\]

The model is identical with its dual. Then the dual problem concerns the plant

\[
    dx^*/dt = f_0x^* + u^*(t), \quad y^*(t) = x^*(t)
\]

and the performance index is

\[
    \int_{t_0}^{t^*} \left[ \frac{1}{2} q_1 [x^*(\tau^*)]^2 + r_0 [u^*(\tau^*)]^2 \right] d\tau^*
\]  

(21)

The discrete-time version of the estimation problem was treated in [11, Example 1]. The dual problem was treated by Rozoer [19].

Example 2. The message is generated as in Example 1, but now it is assumed that two separate signals (mixed with different noise) can be observed. Hence \( \mathbf{R} \) is now a \( 2 \times 2 \) matrix and we assume that

\[
    \mathbf{H} = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}
\]

The block diagram of the model is shown in Fig. 2(a).

Fig. 2 Example 2: Block diagram of message process and optimal filter

Example 3. The message is generated by putting white noise through the transfer function \( 1/(s + 1) \). The block diagram of the model is shown in Fig. 3(a). The system matrices are:

\[
    \mathbf{F} = \begin{bmatrix} 0 & 0 \\ 1 & -1 \end{bmatrix}, \quad \mathbf{G} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \quad \mathbf{H} = \begin{bmatrix} 0 & 1 \end{bmatrix}
\]

In the dual model, the order of the blocks \( 1/s \) and \( 1/(s + 1) \) is interchanged. See Fig. 4. The performance index remains the same as (21). The dual problem was investigated by Kipnis [24].
Example 4. The message is generated by putting white noise through the transfer function $s/(s^2 - f_{12}f_{21})$. The block diagram of the model is shown in Fig. 5(a). The system matrices are:

$$F = \begin{bmatrix} 0 & f_{21} \\ f_{12} & 0 \end{bmatrix}, \quad G = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \quad H = [1 \ 0]$$

The transfer function of the dual model is also $s/(s^2 - f_{21}f_{12})$. However, in drawing the block diagram, the locations of the first and second state variables are interchanged, see Fig. 6. Evidently $f^*_{12} = f_{21}$ and $f^*_{21} = f_{12}$. The performance index is again given by (21).

The message model for the next two examples is the same and is defined by:

$$F = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}$$

The differences between the two examples lie in the nature of the "starting" assumptions and in the observed signals.

Example 5. Following Shinbrot [3], we consider the following situation. A particle leaves the origin at time $t_0 = 0$ with a fixed but unknown velocity of zero mean and known variance. The position of the particle is continually observed in the presence of additive white noise. We are to find the best estimator of position and velocity.

The verbal description of the problem implies that $p_{11}(0) = p_{22}(0) = 0$, $p_{12}(0) > 0$ and $q_{01} = 0$. Moreover, $G = 0$, $H = [1 \ 0]$. See Fig. 7(a).

The dual of this problem is somewhat unusual; it calls for minimizing the performance index

$$p_{21}(0)\{\phi^*(0; x^*, t^*; u^*)\}^2 + \int_{t_0}^{0} p_{11}(u^*,(\tau^*))^2 d\tau^* \quad (t^* < 0)$$

In words: We are given a transfer function $1/s^2$; the input $u^*_1$ over the time-interval $[t^*, 0]$ should be selected in such a way as to minimize the sum of (i) the square of the velocity and (ii) the control energy. In the discrete-time case, this problem was treated in [11, Example 2].

Example 6. We assume here that the transfer function $1/s^2$ is excited by white noise and that both the position $x_1$ and velocity $x_2$ can be observed in the presence of noise. Therefore (see Fig. 8c)
7 Summary of Results: Mathematics

Here we present the main results of the paper in precise mathematical terms. At the present stage of our understanding of the problem, the rigorous proof of these facts is quite complicated, requiring advanced and unconventional methods; they are to be found in Sections 8–10. After reading this section, one may pass without loss of continuity to Section 11 which contains the solutions of the examples.

(1) Canonical form of the optimal filter. The optimal estimate \( \hat{x}(t) \) is generated by a linear dynamical system of the form

\[
\begin{align*}
\frac{d\hat{x}(t)}{dt} & = \begin{bmatrix} h_{tt} & 0 \\ 0 & h_{tt} \end{bmatrix} \hat{x}(t) + \begin{bmatrix} 0 \\ h_{tt} \end{bmatrix} \bar{y}(t) \\
\hat{x}(t) & = \begin{bmatrix} 0 \\ 0 \end{bmatrix} + H(t)\hat{x}(t) \\
\end{align*}
\]

(1)

The initial-state \( \hat{x}(t_0, h_0) \) of (1) is zero.

For optimal extrapolation, we add the relation

\[
\begin{align*}
\hat{x}(t) & \equiv \Phi(t_0, t)\hat{x}(t_0) \\
\end{align*}
\]

(5)

No tables or graphs are known at present for interpolation \( \Phi(t_0, t) \).

The block diagram of (1) and (5) is shown in Fig. 9. The variables appearing in the decision array vectors and the “boxes” represent matrices, operating on vectors. Otherwise (except for the noncommutativity of matrix multiplication), each generalized block diagrams are subject to the same rules as ordinary block diagrams. The fat lines indicating direction of signal flow serve as a reminder that we are dealing with multiple rather than single signals.

The optimal filter (I) is a feedback system. It is obtained by taking a copy of the model of the message process (omitting the constraint at the input), forming the error signal \( \bar{y}(t) \) and feeding the error forward with a gain \( K(t) \). Thus the specification of the optimal filter is equivalent to the computation of the optimal time-varying gain \( K(t) \). This result is general and does not depend on constancy of the model.

(2) Canonical form for the dynamical system governing the optimal error. Let

\[
\ddot{x}(t) = \dot{x}(t) - \ddot{x}(t) \\
\]

(22)

Except for the way in which the excitations enter the optimal error, \( \ddot{x}(t) \) is governed by the same dynamical system as \( \ddot{x}(t) \):

\[
\begin{align*}
\frac{d\ddot{x}(t)}{dt} & = F(t)\ddot{x}(t) + G(t)\theta(t) - K(t)w(t) \\
& \quad + H(t)\ddot{x}(t) \\
\end{align*}
\]

(II)

See Fig. 10.

(3) Optimal gain. Let us introduce the abbreviation:

\[
P(t) = \text{cov}\{\ddot{x}(t), \ddot{x}(t)\} \\
\]

(23)

Then it can be shown that

\[
K(t) = P(t) + F(t)P(t)R^{-1}(t) \\
\]

(III)

(4) Variance equation. The only remaining unknown is \( P(t) \). It can be shown that \( P(t) \) must be a solution of the matrix differential equation

\[
\begin{align*}
\frac{dP}{dt} & = F(t)P + PF(t) - PPH(t)R^{-1}(t)P \\
& \quad + G(t)Q(t)G^T(t) \\
\end{align*}
\]

(IV)
This is the variance equation; it is a system of \( n(n + 1)/2 \) non-linear differential equations of the first order, and is of the Riccati type well known in the calculus of variations \([17, 18]\).

(5) Existence of solutions of the variance equation. Given any fixed initial time \( t_0 \) and a nonnegative definite matrix \( P(t_0) \) (IV) has a unique solution

\[ P(t) = \Phi(t; \theta(t), \theta(t_0)) \]

(24)

defined for all \([t - t_0] \] sufficiently small, taking on the value \( P(t_0) = P_0 \) at \( t = t_0 \). This follows at once from the fact that (IV) satisfies a Lipschitz condition \([21]\).

Since (IV) is nonlinear, we cannot of course conclude without further investigation that a solution \( P(t) \) exists for all \( t \) \([21]\). By taking into account the problem from which (IV) was derived, however, it can be shown that \( P(t) \) in (24) is defined for all \( t \geq t_0 \).

These results can be summarized by the following theorem, which is the analogue of Theorem 3 of \([11]\) and is proved in Section 8:

THEOREM 1. Under Assumptions (A_1), (A_2), (A_3'), the solution of the optimal estimation problem with \( t_0 > -\infty \) is given by relations (1-V). The solution \( P(t) \) of (IV) is uniquely determined for all \( t \geq t_0 \) by the specification

\[ P_0 = \text{cov}[x(t_0), x(t_0)]; \]

knowledge of \( P(t) \) in turn determines the optimal gain \( H(t) \). The initial state of the optimal filter is 0.

(6) Variance of the estimate of a costate. From (23) we have immediately the following formula for (15):

\[ \mathbb{E}[\dot{x}^2(t)] = \|x(t)\|^2 P(t) \]

(25)

(7) Analytic solution of the variance equation. Because of the close relationship between the Riccati equation and the calculus of variations, a closed-form solution of sorts is available for (IV).

The easiest way of obtaining it is as follows \([17]\):

Introduce the quadratic Hamiltonian function

\[ H(x, w, t) = -(1/2)|G'(t)x|^2 + \frac{1}{2}w^2/H(t)w \]

(26)

and consider the associated canonical differential equations

\[ dx/dt = \partial H/\partial w = -F(t)x + H(t)w \]

\[ dw/dt = \partial H/\partial x = G(t)w + F(t)x \]

(27)

We denote the transition matrix of (27) by

\[ \Phi(t, \theta(t), \theta(t_0)) \]

\[ \Theta(t, \theta(t), \theta(t_0)) \]

(28)

In Section 10 we shall prove

THEOREM 2. The solution of (IV) for arbitrary nonnegative definite, symmetric \( P_0 \) and all \( t \geq t_0 \) can be represented by the formula

\[ P(t; \theta(t), \theta(t_0)) = \Theta(t, \theta(t), \theta(t_0))P_0 \Theta(t, \theta(t), \theta(t_0))^{-1} \]

(29)

Unless all matrices occurring in (27) are constant, this result simply replaces one difficult problem by another of similar difficulty, since only in the rarest cases can \( \Theta(t, \theta(t)) \) be expressed in analytic form. Something has been accomplished, however, since we have shown that the solution of nonconstant estimation problems involves precisely the same analytic difficulties as the solution of linear differential equations with variable coefficients.

(8) Existence of steady-state solution. If the time-interval over which data are available is infinite, in other words, if \( t_0 = -\infty \), Theorem 1 is not applicable without some further restriction.

For instance, if \( H(t) = 0 \), the variance of \( \hat{x} \) is the same as the variance of \( x \), if the model (10-11) is unstable, then \( \hat{x}(t) \) defined by (13) does not exist and the estimation problem is meaningless.

The following theorem, proved in Section 9, gives two sufficient conditions for the steady-state estimation problem to be meaningful. The first is the one assumed at the very beginning in the conventional Wiener theory. The second condition, which we introduce here for the first time, is much weaker and more "natural" than the first; moreover, it is almost a necessary condition as well.

THEOREM 3. Denote the solutions of (IV) as in (24). Then the limit

\[ \lim_{t \to \infty} H(t; \theta(t), \theta(t_0)) = \bar{H}(t) \]

exists for all \( t \) and is a solution of (IV) if either

(A_4) the model (10-11) is uniformly asymptotically stable; or

(A_5') the model (10-11) is "completely observable" \([17]\), that is, for all \( t > 0 \) there is some \( t_0 < t \) such that the matrix

\[ M(t_0, t) = \int_0^t \Phi(t, \tau)H(\tau)\Phi(\tau, t)d\tau \]

(31)

is positive definite. (See \([21]\) for the definition of uniform asymptotic stability.)

Remarks. (g) \( \hat{\theta}(t) \) is the covariance matrix of the optimal error corresponding to the very special situation in which (i) an arbitrarily long record of past measurements is available, and (ii) the initial state \( x(t_0) \) was known exactly. When all matrices in (10-12) are constant, then so is \( \hat{\theta} \)—this is just the classical Wiener problem. In the constant case, \( \hat{\theta} \) is an equilibrium state of (IV) (i.e., for this choice of \( \hat{\theta} \), the right-hand side of (IV) is zero). In general, \( \hat{\theta}(t) \) should be regarded as a moving equilibrium point of (IV), see Theorem 4 below.

(h) The matrix \( M(t_0, t) \) is well known in mathematical statistics. It is the information matrix in the sense of R. A. Fisher \([20]\) corresponding to the special estimation problem when (i) \( u(t) = 0 \) and (ii) \( w(t) \) is gaussian with unit covariance matrix. In this case, the variance of any unbiased estimator \( \mu(t) \) of \( [x_0, x(t)] \) satisfies the well-known Cramer-Rao inequality \([20]\).
\[ E[\mu(t) - \bar{\mu}(t)]^2 \geq \|x^s\|^2 M^{-1}(t, t) \]  

Every estimate \( x^* \) has a minimum-variance unbiased estimator for which the equality sign holds in (32) if and only if \( M \) is positive definite. This motivates the use of condition (A*) in Theorem 3 and the term “completely observable.”

(1) It can be shown [17] that in the constant case, a constant observable is equivalent to the easily verified condition:

\[ \text{rank}[H', F' H', \ldots, (F')^{n-1} H'] = n \]  

where the square brackets denote a matrix with \( n \) rows and \( n \) columns.

(1) Stability of the optimal filter. It should be realized now that the optimality of the filter (1) does not at the same time guarantee its stability. The reader can easily check this by constructing an example (for instance, one in which (10-11) consists of two non-interacting systems). To establish weak stability for the filter entails some rather delicate mathematical technicalities which we shall bypass and state only the best final result currently available.

First, some additional definitions.

We say that the model (10-11) is uniformly completely observable if there exist fixed constants, \( \alpha_1, \alpha_2, \alpha_3, \alpha_4 \) and \( \sigma \) such that

\[ \alpha_1 \|x^s\|^2 \leq \|x^s\|^2 M, \quad 0 \leq \alpha_2 \|x^s\|^2 \quad \text{for all} \quad x^s \quad \text{and} \quad t. \]

Similarly, we say that a model is uniformly completely controllable (uniformly completely observable) if the dual model is uniformly completely observable (uniformly completely observable). For a discussion of these notions, the reader may refer to [17]. It should be noted that the property of “uniformity” is always true for constant systems.

We can now state the central theorem of the paper:

**THEOREM 4.** Assume that the model of the message process is

*(A*) uniform nonnegative matrix observable;

*(B*) uniformly completely controllable;

*(C*) \( \|Q(t)\| \leq \alpha_1 \), \( \alpha_1 \leq \|R(t)\| \leq \alpha_4 \) for all \( t > 0 \);

*(D*) \( M(t) \leq \alpha_2 M \).

Then the following is true:

(i) The optimal filter is uniformly asymptotically stable;

(ii) Every solution \( \Pi(t; \mu_0, \nu_0) \) of the variance equation (IV) starting at a symmetric nonnegative matrix \( \Pi(t) \) (defined in Theorem 3) is \( \Pi(t) \) as \( t \to \infty \).

Remarks. (j) A filter which is not uniformly asymptotically stable may have an unbounded response to a bounded input [21]; the practical usefulness of such a filter is rather limited.

(k) Property (ii) in Theorem 4 is of central importance since it shows that the variance equation is a “stable” computational method that may be expected to be rather insensitive to roundoff errors.

(l) The speed of convergence of \( \Pi(t) \) to \( \Pi(t) \) can be estimated quite effectively using the second method of Lyapunov; see [17].

(10) Solution of the classical Wiener problem. Theorems 3 and 4 have the following immediate corollary:

**THEOREM 5.** Assume the hypotheses of Theorems 3 and 4 are satisfied and that \( F, G, H, O, R \) are constants.

Then, if \( \Pi(t) \to \Pi \), the solution of the estimation problem is obtained by solving the right-hand side of (IV) equal to zero and solving the resulting set of quadratic algebraic equations. That solution which is nonnegative definite is equal to \( \Pi \).

To prove this, we observe that, by the assumption of constancy, \( \Pi(t) \) is a constant. By Theorem 4, all solutions of (IV) starting at nonnegative matrices converge to \( \Pi \). Hence, if a matrix \( \Pi(t) \) is found for which the right-hand side of (IV) vanishes and if this matrix is nonnegative definite, it must be identical with \( \Pi \). Note, however, that the procedure may fail if the conditions of Theorems 3 and 4 are not satisfied. See Example 4.

(11) Solution of the Dual Problem. For details, consult [17]. The only facts needed here are the following: The optimal control law is given by

\[ u^*(t^*) = -K^*(t^*)x(t^*) \]

where \( K^*(t^*) \) satisfies the duality relation

\[ K^*(t^*) = K(t) \]

and is to be determined by duality from formula (III). The value of the performance index (20) may be written in the form

\[ \min_{x^*} V(x^*; t^*, b^*, a^*) = \|x^s\|^2 M^{-1}(x^*, x^*, t^*) \]

where \( M(t^*; x^*, b^*, a^*) \) is the solution of the dual of the variance equation (IV).

It should be carefully noted that the hypotheses of Theorem 4 are invariant under duality. Hence essentially the same theory covers both the estimation and the regular problem, as stated in Section 5.

The vector-matrix block diagram for the optimal regulator is shown in Fig. 11.

**Fig. 11** General block diagram of optimal regulator

(12) Computation of the covariance matrix for the message process. To apply Theorem 1, it is necessary to determine \( \{x(t), x(t)\} \). This may be specified as part of the problem statement as in Example 5. On the other hand, one might assume that the message model has reached steady state (see (A4)), in which case from (13) and (12) we have that

\[ S(t) = \text{cov} \{x(t), x(t)\} = \int_{-\infty}^{t} \Phi(t, \tau) G(t, \tau) G(t, \tau) \Phi(t, \tau) d\tau \]

provided the model (10) is asymptotically stable. Differentiating this expression with respect to \( t \) we obtain the following differential equation for \( S(t) \)

\[ dS(t)/dt = F(t)S + SF(t) + G(t)O(t)G(t) \]

This formula is analogous to the well-known lemma of Lyapunov [21] in evaluating the integrated square of a solution of a linear differential equation. In case of a constant system, (36) reduces to a system of linear algebraic equations.

8 Derivation of the Fundamental Equations

We first deduce the matrix form of the familiar Wiener-Hopf integral equation. Differentiating it with respect to time and then using (10-11), we obtain in a very simple way the fundamental equations of our theory.

Much cumbersome manipulation of integrals can be avoided by recognizing, as has been pointed out by Pugachev [27], that the Wiener-Hopf equation is a special case of a simple geometric principle: orthogonal projection.

Consider an abstract space \( R \) such that an inner product \( (X, Y) \) is defined between any two elements \( X, Y \) of \( R \). The norm is defined by \( ||X|| = (X, X)^{1/2} \). Let \( U \) be a subspace of \( R \). We
seek a vector \( U_c \) in \( \mathcal{U} \) which minimizes \( \|X - U\| \) with respect to any \( U \) in \( \mathcal{U} \). If such a minimizing vector exists, it may be characterized in the following way:

**ORTHOGONAL PROJECTION LEMMA.** \( \|X - U\| \geq \|X - U_c\| \) for all \( U \) in \( \mathcal{U} \) if and only if \( (X - U_c, U) = 0 \) for all \( U \) in \( \mathcal{U} \).

(iii) Moreover, if there is another vector \( U^* \) satisfying (37), then \( \|U - U^*\| = 0 \).

**Proof.** (i) Consider the identity

\[ \|X - U\|^2 = \|X - U_c\|^2 + 2(X - U_c, U - U) + \|U - U_c\|^2 \]

Since \( \mathcal{U} \) is a linear space, it contains \( U - U_c \); hence if Condition (37) holds, the middle term vanishes and therefore \( \|X - U\| \geq \|X - U_c\| \). Property (iii) is obvious.

(ii) Supposing that \( (X - U_c, U) = \alpha \neq 0 \). Then

\[ \|X - U_c - \beta U\|^2 = \|X - U\|^2 + 2\alpha \beta + \beta^2 \|U\|^2 \]

For a suitable choice of \( \beta \), the sum of the last two terms will be negative, contradicting the optimality of \( U_c \). Q.E.D.

**WIENER-HOPF EQUATION.** A necessary and sufficient condition for \( [x^*, \hat{x}(t) \{ t \}] \) where \( \hat{x}(t) \) is defined by (14) to be a minimum variance estimator of \( [x^*, x(\tau)] \) for all \( x^* \), is that the matrix function \( \mathbf{A}(t, \tau) \) satisfy the relation

\[ \text{cov}[x(t), x(\tau)] = -\int_t^\tau \mathbf{A}(t, \tau) \text{cov}[x(\sigma), x(\sigma)] d\sigma = 0 \]  

or equivalently

\[ \text{cov}[\hat{x}(t), x(\tau)] = 0 \]  

for all \( \tau \leq \sigma < t \).

**COROLLARY.** \( \text{cov}[x(t), \hat{x}(t)] = 0 \)

**Proof.** Let \( x^* \) be a fixed covariate and denote by \( \mathcal{X} \) the space of all scalar random variables \( [x^*, x(t)] \) of zero mean and finite variance. The inner product is defined as \( (X, Y) = \mathbb{E}[x^* x(t)] \). \( \mathcal{U} \) is the set of all scalar random variables of the type

\[ U = [x^*, u(t)] = \left[ x^*, \int_t^\tau \mathbf{B}(t, \tau) x(\tau) d\tau \right] \]

where \( \mathbf{B}(t, \tau) \) is an \( n \times p \) matrix continuously differentiable in both arguments. We write \( U_c \) for the estimate \( [x^*, \hat{x}(t)] \).

We now apply the orthogonal projection lemma and find that condition (37) takes the form

\[ (X - U_c, U) = \mathbb{E}[x^*, \hat{x}(t)] [x^*, u(t)] = x^* \text{cov}[x(t), u(t)] \]

Interchanging integration and the expected value operation (permissible in view of the continuity assumptions made under (A1), see [28]), we get

\[ (X - U_c, U) = x^* \left\{ \int_t^\tau \text{cov}[x(t, \sigma), x(\sigma)] \mathbf{B}(t, \sigma) d\sigma \right\} x^* \]

This expression must vanish for all \( x^* \). Sufficiency of (39) is obvious. To prove the necessity, we take

\[ \text{cov}[\hat{x}(t), x(\tau)] = \mathbf{A}(t, \tau) \mathbf{R}(\tau) \]

Then \( \mathbf{B}^2 \) is nonnegative definite. By continuity, the integral is positive for some \( x^* \) unless \( \mathbf{B}^2 \) is nonnegative definite. By continuity, the integral will be positive for some \( x^* \) unless \( \mathbf{B}^2 \) and therefore also \( \mathbf{B}(t, \sigma) \) vanishes identically for all \( t \leq \sigma < t \). The Corollary follows by multiplying (39) on the right by \( \mathbf{A}(t, \sigma) \) and integrating with respect to \( \sigma \), Q.E.D.

**Remark.** (a) Equation (39) does not hold when \( a = t \). In fact, \( \text{cov}[\hat{x}(t), x(t)] = 0 \).

For the moment we assume for simplicity that \( t = t \). Differentiating (38) with respect to \( t \) and interchanging \( \partial / \partial t \) and \( \mathbf{E} \), we get for all \( \mathcal{U} \), \( \sigma < t \)

\[ \frac{\partial}{\partial t} \text{cov}[x(t), x(\sigma)] = \mathbf{F}(t) \text{cov}[x(t), x(\sigma)] + \mathbf{G}(t) \text{cov}[u(t), x(\sigma)] \]

and

\[ \frac{\partial}{\partial t} \int_t^\sigma \mathbf{A}(t, \tau) \text{cov}[x(\tau), x(\sigma)] d\tau = \frac{\partial}{\partial t} \int_t^\sigma \mathbf{A}(t, \tau) \text{cov}[y(\tau), y(\sigma)] d\tau + \frac{\partial}{\partial \tau} \mathbf{A}(t, \tau) \mathbf{R}(\sigma) \]

\[ = \int_t^\sigma \frac{\partial}{\partial \tau} \mathbf{A}(t, \tau) \text{cov}[x(\tau), x(\sigma)] d\tau + \mathbf{A}(t, t) \text{cov}[y(t), y(\sigma)] \]

The last term in (41) vanishes because of the independence of \( u(t) \) of \( v(\sigma) \). Q.E.D.

As before, the last term again vanishes. Combining (41-43), we get, bearing in mind also (38),

\[ \int_t^\sigma \left[ \mathbf{F}(t) \mathbf{A}(t, \tau) \mathbf{R}(\tau) \mathbf{A}(t, \tau) \right] \text{cov}[x(\tau), x(\sigma)] d\tau = 0 \]

for all \( \mathcal{U} \), \( \sigma < t \). This condition is certainly satisfied if the optimal operator \( \mathbf{A}(t, \tau) \) is a solution of the differential equation

\[ \mathbf{F}(t) \mathbf{A}(t, \tau) - \frac{\partial}{\partial \tau} \mathbf{A}(t, \tau) - \mathbf{A}(t, \tau) \mathbf{H}(t, \tau) \mathbf{A}(t, \tau) = 0 \]

for all \( \mathcal{U} \), \( \sigma < t \). If \( \mathbf{R}(\tau) \) is positive definite in this interval, then condition (45) is necessary. In fact, let \( \mathbf{B}(t, \tau) \) denote the bracketed term in (44). If \( \mathbf{A}(t, \tau) \) satisfies the Wiener-Hopf equation (38), then \( \hat{x}(t) \) given by (14) is an optimal estimate; and the same holds also for

\[ \hat{x}(t) + \int_t^\tau \mathbf{B}(t, \tau) x(\tau) d\tau \]

since by (44) \( \mathbf{A}(t, \tau) + \mathbf{B}(t, \tau) \) also satisfies the Wiener-Hopf equation. But by the lemma, the norm of the difference of two optimal estimates is zero. Hence

\[ \int_t^\tau \int_t^\tau \mathbf{B}(t, \tau) \text{cov}[x(\tau), x(\sigma)] \mathbf{B}'(t, \tau) d\tau d\sigma x^{**} d\tau d\sigma x^{**} = 0 \]

for all \( x^* \). By the assumptions of Section 4 \( y(\tau) \) and \( v(\tau) \) are uncorrelated and therefore

\[ \text{cov}[x(\tau), x(\sigma)] = \mathbf{R}(\tau) \delta(\tau - \tau') + \mathbf{R}(\tau') \]

Substituting this into the integral (46), the contribution of the second term on the right is nonnegative while the contribution of the first term is positive unless (45) holds (because of the positive definiteness of \( \mathbf{R}(\tau) \)), which concludes the proof.

Differentiating (14), with respect to \( t \) we find

\[ d\hat{x}(t)/dt = \int_t^\tau \frac{\partial}{\partial \tau} \mathbf{A}(t, \tau) x(\tau) d\tau + \mathbf{A}(t, t) x(t) \]

Using the abbreviation \( \mathbf{A}(t, t) = \mathbf{K}(t) \) as well as (45) and (14), we obtain at once the differential equation of the optimal filter:

\[ d\hat{x}(t)/dt = \mathbf{F}(t) \hat{x}(t) + \mathbf{K}(t) x(t) - \mathbf{H}(t) \hat{x}(t) \]  

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Combining (10) and (1), we obtain the differential equation for the error of the optimal estimate:

\[ d\tilde{x}(t)/dt = f(t) - K(t)\dot{H}(t)^T \tilde{x}(t) + G(t)u(t) - K(t)x(t) \] (11)

To obtain an explicit expression for \( K(t) \), we observe first that (39) implies that following identity in the interval \( \theta_0 \leq \sigma < t \):

\[ \text{cov}\, [x(t), x(\sigma)] - \int_0^t A(t, \tau) \text{cov}\, [x(\tau), x(\tau)]d\tau = A(t, \sigma)R(\sigma) \] (39')

Since both sides of (39') are continuous functions of \( \sigma \), it is clear that equality holds also for \( \sigma = t \). Therefore

\[ K(t) = A(t, t)R(t)^{-1} \] (III)

We can now derive the variance equation. Let \( \Psi(t, \tau) \) be the common transition matrix of (1) and (II). Then

\[ P(t) - \Psi(t, t_0)P(t_0)\Psi^T(t, t_0) = \Delta \int_0^t \Psi(t, \tau)[G(\tau)Q(\tau)G(\tau)^T + K(\tau)R(\tau)K(\tau)^T] \Psi^T(t, \tau)d\tau \]

Differentiating with respect to \( t \) and using (III), we obtain after easy calculations the variance equation

\[ dp/dt = f(t)P(t) + P(t)f(t)^T - PH(t)R^{-1}(t)H(t)P + G(t)Q(t)G(t)^T \] (IV)

Alternately, we could write

\[ dp/dt = d \text{cov}\, [\tilde{x}, \tilde{x}] / dt = \text{cov}\, [d\tilde{x}/dt, \tilde{x}] + \text{cov}\, [\tilde{x}, d\tilde{x}/dt] \]

and evaluate the right-hand side by means of (II). A typical covariance matrix to be computed is

\[ \text{cov}\, [\tilde{x}(t), u(t)] = \text{cov}\, \left[ \int_0^t \Psi(t, \tau)[G(\tau)u(\tau) - K(\tau)x(\tau)]d\tau, u(t) \right] = (1/t)G(t)Q(t) \]

the factor \( 1/t \) following from properties of the \( \delta \)-function.

To complete the derivations, we note that, if \( h > t \), then by (3)

\[ x(t) = \Phi(t, t_0)x(t_0) + \int_{t_0}^t \Phi(t, \tau)u(\tau)d\tau \]

Since \( u(\tau) \) for \( t < \tau \leq t \) is independent of \( x(\tau) \) in the interval \( \theta_0 \leq \tau \leq t \), it follows by (38) that the optimal estimator for the right-hand side above is \( 0 \). Hence

\[ \tilde{x}(t, t) = \Phi(t, t)\tilde{x}(t_0) \] (IV)

The same conclusion does not follow if \( h < t \) because of lack of independence between \( x(\tau) \) and \( u(\tau) \).

The only point remaining in the proof of Theorem 1 is to determine the initial conditions for (IV). From (38) it is clear that

\[ \tilde{x}(t, t_0) = 0 \]

Hence

\[ P(t) = \text{cov}\, [\tilde{x}(t, t_0), \tilde{x}(t, t)] = \text{cov}\, [\tilde{x}(t_0), \tilde{x}(t_0)] \]

In case of the conventional Wiener theory (see (A3)), the last term is evaluated by means of (36).

This completes the proof of Theorem 1.

9 Outline of Proofs

Using the duality relations (16), all proofs can be reduced to those given for the regulator problem in [17].

(1) The fact that solutions of the variance equation exist for all \( t \geq t_0 \) is proved in [17, Theorem (6.4)], using the fact that the variance of \( x(t) \) must be finite in any finite interval \( [t_0, t] \).

(2) Theorem 3 is proved by showing that there exists a particular estimate of finite but not necessarily minimum variance. Under (A3), this is proved in [17; Theorem (6.6)]. A trivial modification of this proof goes through also with assumption (A5).

(3) Theorem 4 is proved in [17; Theorems (6.8), (6.10), (7.2)].

The stability of the optimal filter is proved by noting that the estimation error plays the role of a Lyapunov function. The stability of the variance equation is proved by exhibiting a Lyapunov function for \( P \). This Lyapunov function in the simplest case is discussed briefly at the end of Example 1. While this theorem is true also in the nonconstant case, at present one must impose the somewhat restrictive conditions \( A_2 = A_3 \).

10 Analytic Solution of the Variance Equation

Let \( X(t), W(t) \) be the (unique) matrix solution pair for (27) which satisfy the initial conditions

\[ X(t_0) = 1, \quad W(t) = P_0 \] (47)

Then we have the following identity

\[ W(t) = P(t)X(t_0), \quad t \geq t_0 \] (48)

which is easily verified by substituting (48) with (IV) into (27). On the other hand, in view of (47–48), we see immediately from the first set of equations (27) that \( X(t) \) is the transition matrix of the differential equation

\[ dx/dt = -F(t)x + H(t)^T R^{-1}(t)H(t)P(t)x \]

which is the adjoint of the differential equation (IV) of the optimal filter. Since the inverse of a transition matrix always exists, we can write

\[ P(t) = W(t)X^{-T}(t), \quad t \geq t_0 \] (49)

This formula may not be valid for \( t < t_0 \), for then \( P(t) \) may not exist!

Only trivial steps remain to complete the proof of Theorem 2.

11 Examples: Solution

**Example 1.** If \( q_1 > 0 \) and \( r_n > 0 \), it is easily verified that the conditions of Theorems 3–4 are satisfied. After trivial substitutions in (III–IV) we obtain the expression for the optimal gain

\[ k_n(t) = p_n(t)/r_n \] (50)

and the variance equation

\[ dp_n(t)/dt = 2p_n(t)p_n(t) - p_n(t)/r_n + q_n \] (51)
By setting the right-hand side of (51) equal to zero, by virtue of the corollary of Theorem 4 we obtain the solution of the stationary problem (i.e., \( t = -\infty \), see (A1)):

\[
p_{n}(t) = \left[ f_{n} + \sqrt{f_{n}^{2} + q_{n}/r_{n}} \right] r_{n} (52)
\]

Since \( p_{n} \) and \( r_{n} \) are nonnegative, it is clear that only the positive sign is permissible in front of the square root.

Substituting into (50), we get the following expressions for the optimal gain

\[
\hat{e}_{n} = f_{n} + \sqrt{f_{n}^{2} + q_{n}/r_{n}} \tag{53}
\]

and for the infinitesimal transition matrix (i.e., reciprocal time constant)

\[
\hat{f}_{n} = f_{n} - \hat{e}_{n} = -\sqrt{f_{n}^{2} + q_{n}/r_{n}} \tag{54}
\]

of the optimal filter. We see, in accordance with Theorem 4, that the optimal filter is always stable, irrespective of the stability of the message model.

It is easily checked that the formulas (52-54) agree with the results of the conventional Wiener theory [29].

Let us now compute the solution of the problem for a finite smoothing interval \( (t > -\infty) \). The Hamiltonian equations (27) in this case are:

\[
\begin{align*}
\frac{dx}{dt} &= -f_{n}x + 1/(r_{n})w_{n} \\
\frac{dw}{dt} &= q_{n}x + f_{n}w
\end{align*}
\]

Let \( T \) be a matrix of coefficients of these equations.

To compute the transition matrix \( \Theta(t, t_{0}) \) corresponding to \( T \), we note first that the eigenvalues of \( T \) are \( \pm f_{n} \). Using this fact and constancy, it follows that

\[
\Theta(t, t_{0}) = C_{1} e^{t_{0}T} + C_{2} e^{(t - t_{0})T},
\]

where the constant matrices \( C_{1} \) and \( C_{2} \) are uniquely determined by the requirements

\[
\Theta(t_{1}, t_{0}) = \Theta(t_{2}, t_{0}) = I \quad \text{unit matrix}
\]

\[
d\Theta(t, t_{0})/dt|_{t = t_{0}} - T \Theta(t, t_{0}) = \hat{J}_{n} C_{1} - \hat{J}_{n} C_{2}
\]

After a good deal of algebra, we obtain

\[
\Theta(t_{0} + \tau, t_{0}) = \left[ \begin{array}{c}
\cosh \hat{f}_{n}\tau & \frac{f_{n}}{\hat{f}_{n}} \sinh \hat{f}_{n}\tau & \frac{1}{r_{n}\hat{f}_{n}} \sinh \hat{f}_{n}\tau \\
\frac{q_{n}}{\hat{f}_{n}} \sinh \hat{f}_{n}\tau & \cosh \hat{f}_{n}\tau + \frac{f_{n}}{\hat{f}_{n}} \sinh \hat{f}_{n}\tau
\end{array} \right] \tag{55}
\]

Knowledge of \( \Theta(t, t_{0}) \) can be used to derive explicit solutions to a variety of nonstationary filtering problems.

We consider only one such problem, which was treated by Shimbro [3, Example 2]. He assumes that \( f_{n} < 0 \) and that the message process has reached steady-state. From (36) we see that

\[
E_{2}(t) = -q_{n}/2f_{n} \quad \text{for all } t
\]

We assume that the observations of the signal start at \( t = 0 \). Since the estimates must be unbiased, it is clear that \( \hat{f}_{n}(0) = 0 \). Therefore

\[
p_{n}(0) = E_{2}(0) = E_{2}(0) = -q_{n}/2f_{n}
\]

substituting this into (55), we get Shimbro's formula:

\[
p_{n}(t) = q_{n} \left[ (f_{n} - \hat{f}_{n}) e^{-f_{n}t} - (f_{n} + \hat{f}_{n}) e^{-\hat{f}_{n}t} \right] / \left[ (f_{n} - \hat{f}_{n}) e^{f_{n}t} - (f_{n} + \hat{f}_{n}) e^{-\hat{f}_{n}t} \right]
\]

Since \( \hat{f}_{n} < 0 \), we see that as \( t \to -\infty \), \( p_{n}(t) \) converges to

\[
p_{n} = -q_{n}/(f_{n} + \hat{f}_{n}) = (f_{n} - \hat{f}_{n})r_{n}
\]

which agrees with (52).

To understand better the factors affecting convergence to the steady-state, let

\[
\hat{p}_{n}(t) = p_{n}(t) - p_{n}
\]

The differential equation for \( \hat{p}_{n}(t) \) is

\[
\dot{\hat{p}}_{n}(t) = 2|\hat{f}_{n}\hat{p}_{n} - (\hat{p}_{n})^{2}/r_{n} \tag{56}
\]

We now introduce a Lyapunov function [21] for (56)

\[
V(\hat{p}_{n}) = (\hat{p}_{n}/p_{n})^{2}/r_{n} \tag{(57)}
\]

The derivative of \( V \) along motions of (51) is given by

\[
\dot{V}(\hat{p}_{n}) = \frac{\partial V(\hat{p}_{n})}{\partial \hat{p}_{n}} \frac{\partial \hat{p}_{n}}{\partial t} = -2|\hat{p}_{n}|/p_{n} + q_{n}/p_{n} \tag{57}
\]

This shows clearly that the "equivalent reciprocal time constant" for the variance equation depends on two quantities: (i) the message-to-noise ratio \( p_{n}/r_{n} \) at the input of the optimal filter, (ii) the ratio of excitation to estimation error \( q_{n}/p_{n} \).

Since the message model in this example is identical with its dual, it is clear that the preceding results apply without any modification to the dual problem. In particular, the filter shown in Fig. 1(b) is the same as the optimal regulator for a plant with transfer function \( 1/f_{n} \). The Hamiltonian equations (27) for the dual problem were derived by Rosenoer [19] from Pontryagin's maximum principle.

Let us conclude this example by making some observations about the nonconstant case. First, the expression for the derivative of the Lyapunov function given by (57) remains true without any modification. Second, assume \( p_{n}(t) \) has been evaluated somehow. Given this number, \( p_{n}(t) \) can be evaluated for \( t \geq t_{0} \) by means of the variance equation (51); the existence of a Lyapunov function and in particular (57) shows that this computation is stable, i.e., not adversely affected by roundoff errors. Third, knowing \( p_{n}(t) \), equation (56) provides a clear picture of the transient behavior of the optimal filter, even though it might be impossible to solve (51) in closed form.

Example 2. The variance equation is

\[
\begin{align*}
\frac{dp_{n}}{dt} &= 2|\hat{f}_{n}|p_{n} - p_{n}^{2} + q_{n} + q_{n}/p_{n} + q_{n}/r_{n} + q_{n}/r_{n} + q_{n}/r_{n}
\end{align*}
\]

If \( q_{n} > 0, r_{n} > 0, \) and \( r_{2} > 0 \), the conditions of Theorems 3-4 are satisfied. Therefore, the minimum error variance in the steady-state is

\[
p_{n} = \hat{f}_{n} + \sqrt{f_{n}^{2} + q_{n}/r_{n} + q_{n}/r_{n}}
\]

and the optimal steady-state gain are

\[
k_{n} = p_{n}/r_{n}, \quad i = 1, 2
\]

The same problem has been considered also by Westcott [30, Example]. A glance at his calculations shows that ours is the simpler and more natural approach.

Example 3. The variance equation is

\[
\begin{align*}
\frac{dp_{n}}{dt} &= -p_{n}^{2} + q_{n} + q_{n}
\end{align*}
\]

\[
\frac{dp_{n}}{dt} = 2(p_{n} - p_{n}) - p_{n}^{2}/r_{n}
\]

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If \( r_1 = 0 \), the conditions of Theorems 3-4 are satisfied. Solving the right-hand side of (59) equal to zero, we get the solution of the stationary problem:

\[
\begin{align*}
\dot{k}_{10} &= \sqrt{q_{10}/r_{10}}, \\
\dot{k}_{30} &= -1 + \sqrt{1 + 2q_{10}/r_{10}}.
\end{align*}
\]

See Fig. 3(b).

The infinitesimal transition matrix of the optimal filter in the steady-state is:

\[
\Phi = \begin{bmatrix}
0 & -\sqrt{q_{10}/r_{10}} \\
1 & -1 + \sqrt{1 + 2q_{10}/r_{10}}
\end{bmatrix}
\]

The natural frequency of the filter is \((q_{10}/r_{10})^{1/4}\) and the damping ratio is \((1/2)[2 + (r_{10}/q_{10})]^{1/2}\). Even for such a very simple problem, the parameters of the optimal filter are not at all obvious by inspection.

The solution of the dual problem in the steady-state (see Fig. 4) is obtained by utilizing the duality relations

\[
\begin{align*}
\dot{k}_{1*} &= \dot{k}_{10}, \\
\dot{k}_{3*} &= \dot{k}_{30}.
\end{align*}
\]

The same result was obtained by Kipininik [24], using the Euler equations of the calculus of variations.

Example 4. The variance equation is

\[
\begin{align*}
dp_{11}/dt &= 2f_{12}p_{11} - p_{11}r_{11} + q_{11} \\
dp_{12}/dt &= f_{12}p_{11} + 2f_{12}p_{12} - p_{11}p_{12} \\
dp_{21}/dt &= 2f_{12}p_{21} - p_{11}r_{11}
\end{align*}
\]

(59)

If \( f_{12} \neq 0 \), \( f_{12} \neq 0 \), and \( r_{11} > 0 \), the conditions of Theorems 3-4 are satisfied. There are then two possibilities of the right-hand side of (59) to vanish for nonnegative \( p_{12} \):

(A) \( p_{11} = \sqrt{q_{11}/r_{11}} \)

(B) \( p_{11} = \sqrt{q_{11} + 4f_{12}^2/r_{11}} \)

(\( p_{11} = 0 \))

(\( p_{11} = (f_{12}/f_{21}) \sqrt{q_{11}/r_{11}} \))

(\( p_{11} = (f_{12}/f_{21}) \sqrt{q_{11} + 4f_{12}^2/r_{11}} \))

The expression for \( p_{12} \) shows that Case (A) applies when \( f_{12}p_{12} \) is negative (the model is stable but not asymptotically stable) and Case (B) applies when \( f_{12}p_{12} \) is positive (the model is unstable).

The optimal filter is shown in Fig. 5(b). The optimal gains are given by

\[
\begin{align*}
\dot{k}_{11} &= p_{11}/r_{11}, \\
\dot{k}_{31} &= p_{12}/r_{11}
\end{align*}
\]

If \( f_{12} \neq 0 \) but \( f_{12} = 0 \), the model is completely observable but not completely controllable. Hence the steady-state variances exist but the optimal filter is not necessarily asymptotically stable since Theorem 4 is not applicable. As a matter of fact, the optimal filter in this case is partially "open loop" and it is not asymptotically stable.

If \( f_{12} = 0 \), then not even Theorem 3 is applicable. In this case, if \( f_{12} = 0 \), equations (50) have no equilibrium state; if \( f_{12} = 0 \), then equations (50) have an infinity of positive definite equilibrium states given by:

\[
\begin{align*}
p_{11} &= \sqrt{q_{11}/r_{11}}, \\
p_{12} &= 0, \\
p_{13} &= 0.
\end{align*}
\]

Thus if \( f_{12} = 0 \), the conclusions of Theorems 3-4 are false.

Example 5. The variance equation is

\[
\begin{align*}
dp_{11}/dt &= 2p_{11} - p_{11}r_{11} \\
dp_{12}/dt &= p_{12} - p_{11}p_{12}/r_{11} \\
dp_{21}/dt &= -p_{11}p_{21}/r_{11}
\end{align*}
\]

(60)

We assume that \( r_{11} > 0 \); this assures that Theorem 3 is applicable. We then find that the steady-state error variances are all zero. The matrix of coefficients of the Hamiltonian equations (27) is:

\[
T = \begin{bmatrix}
0 & 1/r_{11} & 0 \\
-1 & 0 & 0 \\
0 & 0 & 1 \\
0 & 0 & 0
\end{bmatrix}
\]

and the corresponding transition matrix is (here (4) is a finite series!)

\[
\Theta(t_0 + \tau, t_0) = \begin{bmatrix}
1 & 0 & \tau/r_{11} \\
-\tau & 1 & \tau^2/2r_{11} \\
0 & 0 & 1 \\
0 & 0 & 1
\end{bmatrix}
\]

Using (29), we find \( (p_0 + p_0^2)/t_i \):

\[
\mathbf{p}(t) = \frac{r_{11}p_{11}(0)}{r_{11} + p_{11}(0)t_i/3} \begin{bmatrix} t & t_i \\ t & 1 \end{bmatrix}
\]

This formula, obtained here with little labor, is identical with the results of Shindrot [3, Example 1].

The optimal filter is shown in Fig. 7(b). The time-varying gains tend to 0 as \( t \to \infty \); in other words, the filter pays less and less attention to the incoming signals and relies more and more on the previous estimates of \( r_1 \) and \( r_2 \).

Since the conditions of Theorem 4 are not satisfied, one might suspect that the optimal filter is not uniformly (and hence exponentially [21]) asymptotically stable. To check this conjecture, we calculate the transition matrix of the optimal filter. We find, for \( t, \tau \geq 0 \),

\[
\Psi(t, \tau) = \frac{1}{\alpha(t)} \begin{bmatrix}
\alpha(t) - \beta(t, \tau) & -\alpha(t) + \beta(t, \tau) \\
-\beta(t, \tau) & \alpha(t) + \beta(t, \tau)
\end{bmatrix}
\]

where

\[
\alpha(t) = t^3/3 + r_{11}/p_{11}(0) \\
\beta(t, \tau) = (t^2 - t^2)/2
\]

Since \( \Psi(t, \tau) \) does not converge to zero with \( t - \tau \to \infty \), it is clear that the optimal filter is not even stable, let alone asymptotically stable.

From the transition matrix of the optimal filter, we can obtain at once its impulse response with respect to the input \( z(t_0) \) and output \( z(t) \):

\[
\psi(t_0, t)k_0(\tau) + \psi(t_0, t)k_0(\tau) = \frac{t \tau}{t_i/3 + r_{11}/p_{11}(0)}
\]

This agrees with Shindrot’s result [3].

Example 6. The variance equation is:

\[
\begin{align*}
dp_{11}/dt &= 2p_{11} - p_{11}^2/r_{11} \\
dp_{12}/dt &= p_{12} - p_{11}^2/r_{11} \\
dp_{21}/dt &= -p_{11}p_{21}/r_{11} + q_{11}
\end{align*}
\]

(60)

If \( r_{11} \neq 0 \), \( q_{11} > 0 \), and \( r_{21} > 0 \), then the conditions of Theorems 3-4 are satisfied. Setting the right-hand side of (60) equal to zero leads to a very complicated algebraic problem. We introduce first the abbreviations:

\[
\alpha = |r_{11}| \sqrt{q_{11}/r_{11}} \\
\beta = h_{12}^2q_{11}/r_{12}
\]

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It follows that

\[
\begin{align*}
\alpha_{ik} &= \frac{\alpha^2}{\beta^2} \beta_{ik} = \alpha \sqrt{\frac{2\alpha + \beta^2}{\alpha + \beta^2}} \\
\beta_{ik} &= \frac{\beta^2}{\alpha^2} \beta_{ik} = -\frac{\beta^2}{\alpha^2} \\
\gamma_{ik} &= \frac{\beta^2}{\alpha^2} \beta_{ik} = \frac{\beta^2}{\alpha^2} \\
\delta_{ik} &= \frac{\beta^2}{\alpha^2} \beta_{ik} = \frac{\beta^2}{\alpha^2}.
\end{align*}
\]

It is easy to verify that the right-hand side of (60) vanishes for the set of \( \beta_{ik} \); by Theorem 5, this cannot happen for any other set. Hence the solution of the stationary Wiener problem is complete. It is interesting to note that the conventional procedure would require here the spectral factorization of a two-by-two matrix which is very much more difficult algebraically than by the present method.

The infinitesimal transition matrix of the optimal filter is given by

\[
F_{\text{opt}} = \begin{bmatrix}
-\alpha \frac{\sqrt{2\alpha + \beta^2}}{\alpha + \beta^2} & \alpha \\
-\frac{\beta^2}{\alpha + \beta^2} & -\beta \frac{\sqrt{2\alpha + \beta^2}}{\alpha + \beta^2}
\end{bmatrix}
\]

The natural frequency of the optimal filter is

\[
\omega = |\lambda(F_{\text{opt}})| = \sqrt{\frac{\alpha}{\alpha + \beta^2}}
\]

and the damping ratio is

\[
\zeta = \frac{\text{Re} \lambda(F_{\text{opt}})}{\omega} = \frac{1}{\sqrt{2}} \sqrt{1 + \frac{\beta^2}{2\alpha}}
\]

The quantities \( \alpha \) and \( \beta \) can be regarded as signal-to-noise ratios. Since all parameters of the optimal filter depend only on these ratios, there is a possibility of building an adaptive filter once means of experimentally measuring \( \alpha \) and \( \beta \) are available. An investigation of this sort was carried out by Buey [31] in the simplified case when \( \alpha^2 = \beta^2 = 0 \).

12 Problems Related to Adaptive Systems

The generality of our results should be of considerable usefulness in the theory of adaptive systems, which is as yet in a primitive stage of development.

An adaptive system is one which changes its parameters in accordance with changes in its environment. In the estimation problem, the changing environment is reflected in the time-dependence of \( F, G, H, Q, R \). Our theory shows that such changes affect only the values of the parameters but not the structure of the optimal filter. This is what one would expect intuitively and we now have also a rigorous proof. Under ideal circumstances, the changes in the environment could be detected instantaneously and exactly. The adaptive filter would then behave as required by the fundamental equations (I–IV). In other words, our theory establishes a basis of comparison between actual and ideal adaptive behavior. It is clear therefore that a fundamental problem in the theory of adaptive systems is the further study of properties of the variance equation (IV).

13 Conclusions

One should clearly distinguish between two aspects of the estimation problem:

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