

## Recursive Integral Equations for the Detection of Counting Processes\*

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Communicated by A. V. Balakrishnan

### ABSTRACT

A recursive stochastic integral equation for the detection of counting processes is derived from a previously known formula [5] of the likelihood ratio. This is done quite simply by using a result due to Doléans-Dade [4] on the solution of stochastic integral equations.

**1. Introduction.** Recently modern martingale theory has been used to describe Counting Processes (hereafter abbreviated CP) in a way specially appropriate to the problems of detection and filtering. This has given rise to the notion of Integrated Conditional Rate (ICR) [5], which generalizes the notion of random rate.

Expressions for likelihood ratios (involving ICR's) for the detection of CP's have been obtained in [5] using a three-step technique introduced by Kailath [9] and Duncan ([6], [7]) in their works on detection of a stochastic signal in white noise. The three steps are the Likelihood Ratio Representation Theorem ([2], [5], [6]), the Girsanov Theorem ([5], [8], [13]) and the Innovation Theorem ([2], [5], [9]). By this method likelihood ratios for a large class of CP's can be found. These expansions represent a generalization of the formulas given in [1] and [12]

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\*Research sponsored by the Air Force Office of Scientific Research, AFSC, USAF, under Grant no. AFOSR-70-1920C, and the National Science Foundation under Grant no. GK-20385 and ENG 75-20223.

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in the context of Poisson processes and [2] in the context of CP's which admit a conditional rate.

The purpose of this paper is not to present a proof of the likelihood ratio formula (for that see [5]) but to derive from this formula stochastic integral equations by which the likelihood ratio can be computed recursively. This can be done quite simply using a result due to Doléans–Dade [4] on the solution of stochastic integrals equations involving semimartingales. These recursive equations are most useful in applications as they give a way of implementing the computation of the likelihood ratio continuously in time.

**2. Preliminaries.** Let  $(\Omega, \mathcal{F}, P)$  be a complete probability space. By  $(X_t)$  we denote a real valued stochastic process defined on  $\mathbf{R}_+$ , the positive real line and by a Counting Process (CP) we mean

**Definition 2.1.** A CP is a stochastic process having sample paths which are zero at the time origin and consisting of right-continuous step functions with positive jumps of size one.

The time of  $n^{\text{th}}$  jump  $J_n$  of a CP  $(N_t)$  is the stopping time defined by

$$J_n = \begin{cases} \inf\{t: N_t \geq n\} \\ \infty \text{ if the above set is empty.} \end{cases}$$

Let  $(\mathcal{F}_t)$  be a right-continuous increasing family of  $\sigma$ -subalgebras of  $\mathcal{F}$  with  $\mathcal{F}_0$  containing all the  $P$  negligible sets, and suppose  $(N_t)$  is a CP, adapted to  $\mathcal{F}_t$ , with the sole assumption that  $EN_t$  is finite for each  $t$ . Then, as a consequence of the Doob–Meyer decomposition for supermartingales we can associate to  $(N_t)$  a unique *natural increasing process*  $(A_t)$ , dependent on the family  $(\mathcal{F}_t)$ , which makes the process  $(M_t \triangleq N_t - A_t)$  a martingale (see [11]). This decomposition  $(N_t = M_t + A_t)$  is intuitively a decomposition into the part  $(M_t)$  which is not predictable and  $(A_t)$  which can be perfectly predicted. This unique process  $(A_t)$  is called the *Integrated Conditional Rate* (ICR) of  $(N_t)$  with respect to  $(\mathcal{F}_t)$  (“the  $(\mathcal{F}_t)$  ICR of  $(N_t)$ ”) and has been studied in [5]. The terminology ICR is motivated by the fact that when  $(N_t)$  satisfies some sufficiency conditions its ICR takes on the form  $(\int_0^t \lambda_s ds)$  where  $(\lambda_t)$  is a nonnegative process called the *conditional rate* (with respect to  $(\mathcal{F}_t)$ ) satisfying  $\lambda_t = \lim_{h \rightarrow 0} E[h^{-1}(N_{t+h} - N_t) | \mathcal{F}_t]$  ([5], Section 2.5). The existence of CP's possessing a bounded conditional rate with respect to the family of  $\sigma$ -algebras generated by the process itself has been first shown in [2] and in [5]. Sufficiency conditions for the existence of a conditional rate have been given in [5]. By a change of time we can show similar results (i.e., existence (see [5], Corollary 3.1.3) and sufficiency conditions) for  $(\mathcal{F}_t)$  ICR's of the form  $(\int_0^t \lambda_s dm_s)$  where  $(\lambda_t)$  is a *locally bounded predictable process* and  $m_t$  a *deterministic increasing right-continuous function* with  $m_0 = 0$ . Denote by  $\mathcal{H}(\mathcal{F}_t)$  the class of all locally bounded predictable (with respect to  $(\mathcal{F}_t)$ ) processes (see [3], p. 98). For example, processes adapted to  $(\mathcal{F}_t)$  and having left-continuous sample paths belong to  $\mathcal{H}(\mathcal{F}_t)$ .

**Remark 2.2.** Let the ICR  $(A_t)$  be of the form  $(\int_0^t \lambda_s dm_s)$  and denote by  $\Lambda$  the union of all intervals of  $\mathbf{R}_+$  on which the function  $m_t$  is constant. Observe that the ICR  $(A_t)$  is not affected by a change of values of  $(\lambda_t)$  for  $t \in \Lambda$  and we may well have  $\lambda_t = \infty$  for  $t \in \Lambda$ . To avoid problems due to this indeterminacy we adopt the following convention: for  $t \in \Lambda$  we set  $\lambda_t$  equal to unity.

We assume here that modern martingale theory ([11], [3]) is known. Recall that a *semimartingale*  $(X_t)$  is a process which can be written as a sum  $(X_t = X_0 + L_t + A_t)$  where  $X_0$  is  $\mathcal{F}_0$ -measurable,  $(L_t)$  is a  $(\mathcal{F}_t)$  local martingale and  $(A_t)$  is a right-continuous process adapted to  $(\mathcal{F}_t)$  having sample paths of bounded variation on every finite interval and with  $A_0 = 0$  a.s. (see [3]). A result basic to this study and due to Doléans–Dade [4] is the following: the stochastic integral equation

$$Z_t = 1 + \int_0^t Z_{s-} dX_s$$

where  $(X_t)$  is a semimartingale has a unique solution, which is a semimartingale given by<sup>†</sup>

$$Z_t = \exp\left(X_t - \frac{1}{2} \langle X^c \rangle_t\right) \prod_{s \leq t} (1 + \Delta X_s) \exp(-\Delta X_s)$$

where the product in the right hand side converges a.s. for each  $t$ . Here we define  $(\langle X^c \rangle_t)$  as the *unique natural increasing process* (see [3]) associated to the continuous part of the *local martingale*  $(L_t)$ ;  $(\langle X^c \rangle_t)$  is identically zero when  $(X_t)$  is a semimartingale with sample paths of bounded variation on every finite interval (see [3]).

**3. The Detection Problem.** Let  $P_0$  and  $P_1$  be two measures carried on  $(\Omega, \mathcal{F})$ . Suppose that  $(N_t)$  is a CP defined on  $(\Omega, \mathcal{F})$  and denote by  $\mathcal{N}_t$  the minimal  $\sigma$ -algebra generated by  $(N_t)$  up to and at time  $t$ . The notation  $E_i(\cdot)$  for  $i=0, 1$  is intended for the expectation operator with respect to the measure  $P_i$ .

**Definition 3.1.** For a  $(\mathcal{N}_t)$  stopping time  $R$  (possibly infinite) denote by  $\bar{P}_i^R$  for  $i=0, 1$  the restriction of the measure  $P_i$  to the  $\sigma$ -algebra  $\mathcal{N}_R$ .

We have the inclusion  $\mathcal{N}_R \subset \mathcal{F}$  so that if  $P_0 \ll P_1^*$  then  $\bar{P}_0^R \ll \bar{P}_1^R$  and the Radon–Nikodym derivative  $d\bar{P}_0^R/d\bar{P}_1^R$  is well defined. We examine now the meaning of this Radon–Nikodym derivative. In the case where the stopping time  $R$  is equal to a constant  $a$  then  $\mathcal{N}_R = \mathcal{N}_a = \sigma(N_u, 0 \leq u \leq a)$  so that  $d\bar{P}_0^a/d\bar{P}_1^a$  is the likelihood ratio for testing the two hypotheses  $H_i$  for  $i=0, 1$ :  $P_1$  is the probability measure on  $(\Omega, \mathcal{F})$ , by observations on the CP  $(N_t)$  for  $t \leq a$ . The detection scheme then consists in selecting  $H_0$  or  $H_1$  according as  $d\bar{P}_0^a/d\bar{P}_1^a$  is above or below a given threshold. Now in the case where  $R$  is a stopping time

<sup>†</sup>When  $f_t$  is a right-continuous function with left-hand limits  $\Delta f_t$  denotes the jump  $f_t - f_{t-}$ .

\* $P_0 \ll P$  means that the measure  $P_0$  is absolutely continuous with respect to  $P$  while  $P_0 \sim P$  indicates that the two measures are equivalent.

which is not a constant we know that  $\mathcal{U}_R \supset \sigma(N_{u \wedge R}, 0 \leq u)$  (this follows from the fact that  $N_{u \wedge R}$  is  $(\mathcal{U}_R)$  measurable by Theorem 49-IV of [11]) but the reverse inclusion is not necessarily true. For this reason  $d\bar{P}_0^R/d\bar{P}_1^R$  is not the likelihood ratio for our detection problem when the time of observation is the stochastic interval  $[0, R]$ , as one could have conjectured. But one can interpret  $d\bar{P}_0^R/d\bar{P}_1^R$  as a likelihood ratio if we assume that the information accessible to the observer is  $\mathcal{U}_R$  and not simply  $\sigma(N_{u \wedge R}, 0 \leq u)$ . For  $i=0, 1$  with the measure  $P_i$  carried on  $(\Omega, \mathcal{F})$  suppose that the CP  $(N_t)$  has the process  $(\int_0^t \lambda_s^i dm_s)$  for  $(\mathcal{F}_t^i)$  ICR, where  $(\mathcal{F}_t^i)$  is a family of  $\sigma$ -algebras with  $\mathcal{F}_t^i \supset N_t, (\lambda_t^i) \in \mathcal{H}(\mathcal{F}_t^i)$  is a positive process, and  $m_t$  is an increasing deterministic function with  $m_0=0$ .

It is known that we can make a change of measure under which  $(N_t)$  is a CP of independent increments with mean  $m_t = EN_t$  under the new measure  $P$  (Theorem 2.6.1 of [5]). Using this fact and the three-step technique of Duncan and Kailath (see Introduction) the likelihood ratio for detecting CP's has been obtained according to

**Theorem 3.2** (Theorem 3.4.4 of [5]). *For  $i=0, 1$  let  $(N_t)$  be, under the measure  $P_i$ , the CP described above. Assume*

- (a)  $P_0 \ll P$  and  $P \sim P_1$  and define for  $i=0, 1$  the  $(P, \mathcal{U}_t)$  martingale

$$L_t^i = E \left[ \frac{d\bar{P}_i^\infty}{d\bar{P}^\infty} \middle| \mathcal{U}_t \right];$$

- (b) For  $i=0, 1$ , the stopping times  $T^i$  are such that there exists increasing sequences of stopping times  $(T_n^i)$  for which  $T^i = \lim_n T_n^i$  a.s. and  $E(\ln^- L_{T_n^i}^i)^2 < \infty$  for each  $n$ . Let  $T = T^1 \wedge T^0$ ;

- (c) For  $i=0, 1$   $E_i \int_0^{t \wedge T} \lambda_s^i dm_s < \infty$ .

Then

$$\frac{d\bar{P}_0^{t \wedge T}}{d\bar{P}_1^{t \wedge T}} = \prod_{J_n \leq t \wedge T} \left[ \frac{\hat{\lambda}_{J_n}^0}{\hat{\lambda}_{J_n}^1} \right] \exp \left[ \int_0^{t \wedge T} (\hat{\lambda}_s^1 - \hat{\lambda}_s^0) dm_s \right] \tag{1}$$

where  $\hat{\lambda}_t^i \triangleq E_i(\lambda_t^i | \mathcal{U}_t)$  for  $i=0, 1$  and  $J_n$  is the time of  $n^{th}$  jump of  $(N_t)$ . By convention the product  $\prod(\cdot) = 1$  for  $J_1 > t \wedge T$ .

*Remark 3.3.* (a) The stopping time  $T^i$  which is the first time after which the martingale  $(L_t^i)$  can behave badly may take the value  $+\infty$ . It is in fact desirable for  $T^i$  to be as large as possible.

(b) By our convention (Remark 2.2) condition (c) above insures that the process  $(\hat{\lambda}_t^i)$  is well defined.

**4. Recursive Integral Equations for Likelihood Ratios** We show here that the likelihood ratio (1) of our detection problem can be obtained as the unique solution of a stochastic integral equation. This stochastic integral equation can be mechanized by a feedback scheme tantamount to a recursive filter, as shown in Figure 1.

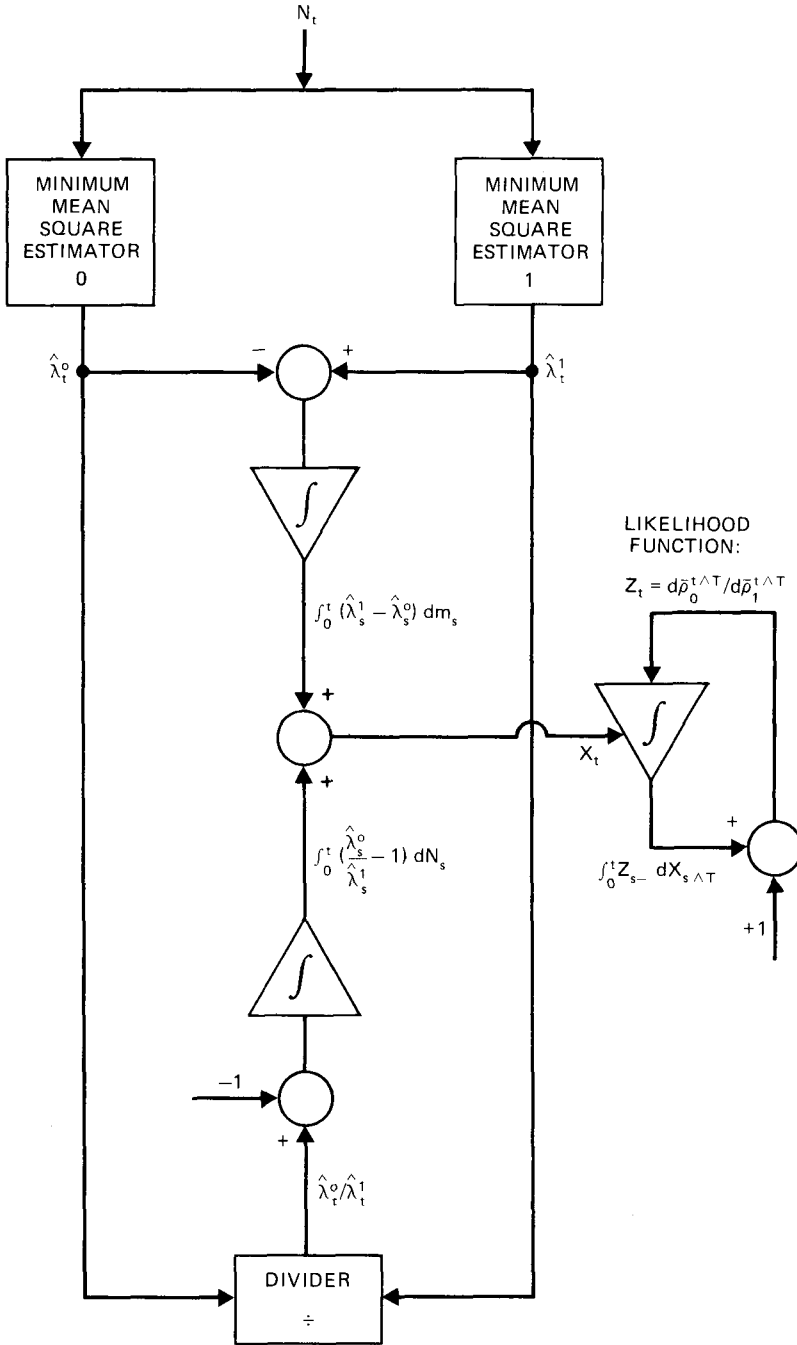


Figure 1. Recursive Scheme for Obtaining the Likelihood Function  $Z^t$

**Theorem 4.1.** *The likelihood ratio  $d\bar{P}_0^{t\wedge T}/d\bar{P}_1^{t\wedge T}$  of Theorem 3.2 is the unique solution of the following stochastic integral equation:*

$$Z_t = 1 + \int_0^t Z_{s-} dX_{s\wedge T} \quad (2)$$

where

$$X_t = \int_0^t \left\{ \left[ \frac{\hat{\lambda}_s^0}{\hat{\lambda}_s^1} \right] - 1 \right\} dN_s + \int_0^t (\hat{\lambda}_s^1 - \hat{\lambda}_s^0) dm_s \quad (3)$$

*Proof.* By assumption  $(\lambda_t^i), i=0, 1$ , is positive a.s. finite for all  $t$  (by condition (c) of Theorem 3.2 and Remark 2.2). The process  $(N_t)$  has a finite number of jumps in any finite interval so that the process  $(\int_0^{t\wedge T} [(\hat{\lambda}_s^0/\hat{\lambda}_s^1) - 1] dN_s)$  has sample paths of bounded variation on any finite interval; and so does the process  $(\int_0^{t\wedge T} (\hat{\lambda}_s^1 - \hat{\lambda}_s^0) dm_s)$  by assumption (c) of Theorem 3.2. Hence  $(X_{t\wedge T})$  is a semimartingale with sample paths of bounded variation on any finite interval so that  $(\langle X^c \rangle_{t\wedge T}) \equiv 0$  (see the remark, on p. 90, following proposition 3 of [3]). Then by Theorem 1 of [4] the unique solution of (2) is given by

$$Z_t = \exp(X_{t\wedge T}) \prod_{s \leq t} (1 + \Delta X_{s\wedge T}) \exp(-\Delta X_{s\wedge T}) \quad (4)$$

Now  $\Delta X_{s\wedge T} = ((\hat{\lambda}_s^0/\hat{\lambda}_s^1) - 1)\Delta N_{s\wedge T}$  and hence the product in (4) becomes

$$\begin{aligned} \prod_{s \leq t} (\cdot) &= \prod_{s \leq t} \left[ 1 + \left[ \frac{\hat{\lambda}_s^0}{\hat{\lambda}_s^1} - 1 \right] \Delta N_{s\wedge T} \right] \exp \left[ \sum_{s \leq t\wedge T} - \left[ \frac{\hat{\lambda}_s^0}{\hat{\lambda}_s^1} - 1 \right] \Delta N_{s\wedge T} \right] \\ &= \prod_{J_n \leq t\wedge T} \left[ \frac{\hat{\lambda}_{J_n}^0}{\hat{\lambda}_{J_n}^1} \right] \exp \left[ - \int_0^{t\wedge T} \left[ \frac{\hat{\lambda}_s^0}{\hat{\lambda}_s^1} - 1 \right] dN_s \right] \end{aligned}$$

Substituting the above relation and expression (3) in (4) gives the desired result (compare with (1))

$$Z_t = \prod_{J_n \leq t\wedge T} \left[ \frac{\hat{\lambda}_{J_n}^0}{\hat{\lambda}_{J_n}^1} \right] \exp \left[ \int_0^{t\wedge T} (\hat{\lambda}_s^1 - \hat{\lambda}_s^0) dm_s \right] = \frac{d\bar{P}_0^{t\wedge T}}{d\bar{P}_1^{t\wedge T}}. \quad \square$$

Observe that if under the measure  $P_1$  the CP  $(N_t)$  is a process of independent increments with mean  $m_t$ , then  $P \equiv P_1, \lambda_t^1 = 1$  and Eq. (3) becomes

$$X_t = \int_0^t (\hat{\lambda}_s^0 - 1) d(N_s - m_s) \quad (5)$$

The process  $(M_t \stackrel{\Delta}{=} N_t - m_t)$  is a  $(P, \mathcal{F}_t)$  martingale. Hence (5) shows that the process  $(X_{t \wedge T})$  is a local martingale. In turn, (2) then implies that the process  $(Z_t)$  is a local martingale. In this case we in fact have  $Z_t = E_1[(dP_0^\infty/dP_1^\infty)|\mathcal{F}_{t \wedge T}]$ , i.e. the likelihood function is a uniformly integrable martingale.

In applications, Eqs. (2) and (3) give a way of implementing the computation of the likelihood ratio continuously in time. They represent recursive equations if one also obtains the best estimates  $(\hat{\lambda}_t^i)$  in a recursive manner. The block diagram of this implementation is given in Figure 1.

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(Received October 6, 1975)