

## A NOTE ON STATE ESTIMATION FROM DOUBLY STOCHASTIC POINT PROCESS OBSERVATION

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### 0. Introduction

In this note we study a state estimation of a Markovian semimartingale from a doubly stochastic point process observation.

All stochastic processes below are supposed to be defined on a filtered probability space  $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \geq 0}, P)$  where  $(\mathcal{F}_t)$  is a filtration satisfying usual conditions.

Consider a state estimation problem where the signal process is a real-valued continuous semimartingale  $X$  that is also a Markov process given by

$$X_t = X_0 + \int_0^t H_s ds + B_t, \quad t \in \mathbb{R}^+, \quad (0.1)$$

where  $H_t$  is a continuous process and  $B_t$  is a standard Brownian motion, and the observation is a doubly stochastic point process  $N_t$  driven by  $X_t$ :  $N_t$  is a point process of intensity  $\lambda_t = \lambda(X_t)$  where  $\lambda$  is a nonnegative boolean function.

Denote by  $Z_t^u$  the process  $\exp(iuX_t)$ . We want to investigate the best state estimation

$$\pi_t(Z_t^u) = E[Z_t^u | \mathcal{F}_t^N] \quad (0.2)$$

where  $\mathcal{F}_t^N$  is the natural filtration of the process  $N_t$  i.e.  $\mathcal{F}_t^N = \sigma(N_s, s \leq t)$ . In the sequel the notation  $\pi_t(\dots)$  stands for the conditional expectation given  $\mathcal{F}_t^N$ .

### 1. A stochastic differential equation for the best state estimation of $Z_t^u$

**Theorem 1.**  $\pi_t(Z_t^u)$  satisfies the following equation:

$$\begin{aligned} \pi_t(Z_t^u) = & E[Z_0^u] + iu \int_0^t \pi_s(Z_s^u H_s) ds - \frac{u^2}{2} \int_0^t \pi_s(Z_s^u) + \\ & + \int_0^t \lambda_s^{-1} \pi_s[(Z_s^u - \pi_s(Z^u))(\lambda_s - \pi_s(\lambda_s))](dN_s - \pi_s(\lambda_s) ds) \end{aligned} \quad (1.1)$$

**Proof.** Applying the Ito formula to  $z_t^u = \exp(iuX_t)$  we have

$$Z_t^u = Z_0^u + \int_0^t \left( iuH_s - \frac{u^2}{2} \right) ds + iu \int_0^t Z_s^u dB_s.$$

$Z_t^u$  is in fact a semimartingale, and the filtering equation from point process observation [2] applied to  $Z_t^u$ :

$$\begin{aligned} Z_t(Z^u) &= E[Z_0^u] + \int_0^t \pi_s \left[ Z_s^u \left( iuH_s - \frac{u^2}{2} \right) \right] ds + \\ &+ \int_0^t \pi_s^{-1}(\lambda) [\pi_s(Z^u \lambda_s) - \pi_s(Z_s^u) \pi_s(\lambda_s)] [dN_s - \pi_s(\lambda_s) ds]. \end{aligned}$$

Now

$$\begin{aligned} &\pi_s \{ [Z_s^u - \pi_s(Z_s^u)] [\lambda_s - \pi_s(\lambda_s)] \} = \\ &= \pi_s [Z_s^u \lambda_s - Z_s^u \pi_s(\lambda_s) - \pi_s(Z_s^u) \lambda_s + \pi_s(Z_s^u) \pi_s(\lambda_s)] = \\ &= \pi_s (Z_s^u \lambda_s) - \pi_s [Z_s^u \pi_s(\lambda_s)] - \pi_s [\pi_s(Z_s^u) \lambda_s] + \pi_s(Z_s^u) \pi_s(\lambda_s). \end{aligned} \quad (1.2)$$

It follows from

$$\begin{aligned} \pi_s [Z_s^u \pi_s(\lambda_s)] &= E[Z_s^u E(\lambda_s | \mathcal{F}_s^N) | \mathcal{F}_s^N] = \\ &= E(\lambda_s | \mathcal{F}_s^N) E(Z_s^u | \mathcal{F}_s^N) = \pi_s(\lambda_s) \pi_s(Z^u), \end{aligned}$$

and also from

$$\pi_s [\pi_s(Z_s^u) \lambda_s] = \pi_s(Z_s^u) \pi_s(\lambda_s)$$

that it remains only the first and the second terms in the left hand side of (1.2) and we have:

$$\pi_s(Z_s^u \lambda_s) - \pi_s(Z_s^u) \pi_s(\lambda_s) = \pi_s [(Z_s^u - \pi_s(Z_s^u)) (\lambda_s - \pi_s(\lambda_s))]$$

and the equation (1.1) is thus completely proved.

**Remark.** In the multidimensional case, the signal process is a vector process given by

$$X_t = X_0 + \int_0^t H_s ds + B_t$$

where  $X, H, B$  are multidimensional process. By  $Z_t^u$  we denote now the process  $\exp(i\langle u, X_t \rangle)$ , where  $u = (u_1, \dots, u_n) \in \mathbb{R}^n$ ,  $X_t = (X_t^1, \dots, X_t^n)$  and  $\langle \cdot, \cdot \rangle$  stands for the

scalar product in  $\mathbb{R}^n$ . And the best state estimation for  $Z_t^u$  based on an observation process that is a doubly stochastic point of intensity  $\lambda_t = \lambda(X_t)$  is

$$\pi_t(Z_t^u) \equiv E[Z_t^u | \mathcal{F}_t^N] = E[\exp i\langle u, X_t \rangle | \mathcal{F}_t^N]. \quad (1.3)$$

The stochastic differential equation for  $\pi_t(Z_t^u)$  is the same as (1.1) with  $Z_t^u = \exp\langle u, X_t \rangle$ .

In the next Section, we will establish a connection between the characteristic function of  $X_t$  and the filter of  $Z_t^u$  and so we will see that the laws of the signal  $X_t$  can be completely determined by  $\pi_t(Z_t^u)$ .

## 2. Characteristic function of $X_t$

Put

$$\psi_t(u) = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} E[\exp(iu\Delta X_t) - 1 | X_t] \quad (2.1)$$

is the limit in the right hand side exists, where  $E[\cdot | X_t]$  is the conditional expectation given  $X_t$ .

Denote by  $\varphi_t(u)$  the characteristic function of  $X_t$ :

$$\varphi_t(u) = E[\exp(iuX_t)] = E[Z_t^u].$$

We note that

$$\begin{aligned} \varphi_{t+\Delta t}(u) &= E[\exp(iuX_{t+\Delta t})] = E[\exp iu(X_t + \Delta X_t)] = \\ &= E[\exp(iuX_t \exp iu\Delta X_t)] = \\ &= E[\exp(iuX_t E(\exp iu\Delta X_t | X_t))] \\ \varphi_{t+\Delta t}(u) - \varphi_t(u) &= E\{(\exp(iuX_t)E[\exp iu\Delta X_t - 1 | X_t])\} \end{aligned}$$

It follows that

$$\frac{\partial \varphi_t(u)}{\partial t} = \lim_{\Delta t \downarrow 0} E \left\{ (\exp iuX_t) \frac{1}{\Delta t} E[\exp iu\Delta X_t - 1 | X_t] \right\}.$$

We have now:

$$\frac{\partial \varphi_t(u)}{\partial t} = E[Z_t^u \psi_t(u)] \quad (2.2)$$

$$\varphi_0(u) = E[Z_0^u]$$

Next, we denote by  $\mathcal{F}_{t-\varepsilon}^N$  the  $\sigma$ -algebra generated by all  $N_s$ ,  $s \leq t - \varepsilon$  for all small  $\varepsilon > 0$ . In noticing that by definition (2.1)  $\psi_t(u)$  is conditioning to the random variable  $\chi_t$  so it is independent of  $\mathcal{F}_{t-\varepsilon}^N$  and we have:

$$E[Z_t^u \psi(u)] = E[E(Z_t^u \psi(u) | \mathcal{F}_{t-\varepsilon}^N)] = E[\psi_t(u) E(Z_t^u | \mathcal{F}_{t-\varepsilon}^N)].$$

Because of the left continuity of  $(\mathcal{F}_t^N)$  we have by letting  $\varepsilon \rightarrow 0$

$$E[Z_t^u \psi_t(u)] = E[\psi_t(u) E(Z_t^u | \mathcal{F}_t^N)] = E[\psi_t(u) \pi_t(Z_t^u)]$$

then we have the following

**Proposition 1.** *The law of the signal  $X_t$  can be determined in term of filtering by the following equation:*

$$\frac{\partial \varphi_t(u)}{\partial t} = E[\psi_t(u) \pi_t(Z_t^u)] \tag{2.3}$$

$$\varphi_0(u) = E[Z_0^u]$$

We will see in next Section that  $X_t$  can be recognized by filtering and the process  $H_t$ .

### 3. An expression of the function $\psi_t(u)$

The equation (1.1) can be rewritten as:

$$dX_t = H_t dt + dB_t \tag{3.1}$$

or

$$\Delta X_t = H_t \Delta t + \Delta B_t \tag{3.2}$$

where  $\Delta X_t = X_{t+\Delta t} - X_t$ ,  $\Delta B_t = B_{t+\Delta t} - B_t$ ,  $B_t$  is a Brownian motion and since  $EB_t B_s = \min(t, s)$ , we have

$$E[\exp iu \Delta X_t - 1 | X_t] = \exp[iu H_t(X_t) \Delta t] E[\exp iu \Delta B_t | X_t] - 1$$

It follows from the fact that  $\Delta B_t$  is normally distributed with mean 0 and covariance  $\Delta t$

$$E[iu \Delta B_t | X_t] = \exp \left[ -\frac{1}{2} u^2 \Delta t \right].$$

Hence,

$$\begin{aligned}\psi_t(u) &= \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} E[\exp iu\Delta X_t - 1 | X_t] = \\ &= \exp\left(iuH_t - \frac{u^2}{2}\right)\end{aligned}$$

or

$$\psi_t(u) = \exp\left(iuH_t - \frac{u^2}{2}\right). \quad (3.3)$$

A substitution of this expression of  $\psi_t$  into (2.3) yields

**Proposition 2.**

$$\frac{\partial \varphi_t(u)}{\partial t} = E\left\{\left[\exp\left(iuH_t - \frac{u^2}{2}\right)\right] \pi_t(Z_t^u)\right\} \quad (3.4)$$

$$\varphi_0(u) = E[Z_0]$$

#### 4. A Bayes formula for the best state estimation of $Z_t^u$

We know that by a change of reference probability  $P \rightarrow Q$  such that  $P_t \ll Q_t$  for all restriction  $P_t$  and  $Q_t$  of  $P$  and  $Q$  respectively to  $(\Omega, \mathcal{F}_t)$ , we have [1]

$$E_P[U_t | \mathcal{G}_t] = \frac{E_Q[U_t L_t | \mathcal{G}_t]}{E_Q[L_t | \mathcal{G}_t]}$$

where  $U_t$  is a real-valued bounded process adapted to  $\mathcal{F}_t$ ,  $\mathcal{G}_t$  is any sub  $\sigma$ -field of  $\mathcal{F}_t$  :  $\mathcal{G}_t \subset \mathcal{F}_t$  and  $L_t = \frac{dP_t}{dQ_t}$ .

Now, for a doubly stochastic point process  $Y_t$  of intensity  $\lambda_t = \lambda(X_t)$  we have

$$L_t = \left( \prod_{0 \leq s \leq t} \lambda(X_s) \Delta N_s \right) \exp \left\{ \int_0^t (1 - \lambda(X_s)) ds \right\}.$$

We note that under  $Q$  the process  $N_t$  is a Poisson process of intensity 1. And we have

$$\pi_t(Z_t^u) = \frac{E_Q[Z_t^u L_t | \mathcal{F}_t^N]}{E_Q[L_t | \mathcal{F}_t^N]} = \frac{E_Q[L_t \exp iuX_t | \mathcal{F}_t^N]}{E_Q[L_t | \mathcal{F}_t^N]}.$$

#### References

- [1] Alan F. Karr, *Point Processes and Their Statistical Inference*, Second Edition, Marcel Dekker, Inc, 1991.
- [2] Tran Hung Thao, *Note on Filtering from Point Processes*, Acta Mathematica, Volume 16, No.1, 1991, 39-47.

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