

Numerical analysis for some stochastic delay differential equations

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Abstract

In this paper we study the numerical solution of the stochastic delay differential equations of the following form

$$du(x, t) = f(x, t, u(x, t - \tau)) dt + g(x, t, u(x, t), u(x, t - \tau)) dW(t), \quad t \in [0, T]$$

$$u(x, t) = \Psi(x, t), \quad t \in [-\tau, 0]$$

(with the lag $\tau > 0$) where $x \in R^v$, (R^v is the v – dimensional Euclidean space). Here $u \in R^n$, $W(t)$ is an n -dimensional Wiener process given on the filtered probability space (Ω, F, P) ,

$$f : R^{n+v+1} \rightarrow R^n, g : R^{n+v+1} \rightarrow R^{n \times n} \text{ and } \Psi : R^v \times [-\tau, 0] \rightarrow R^n.$$

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1. Introduction

Let $(\Omega, F, \{F_t\}_{t \geq 0}, P)$ be a complete probability space with the filtration $\{F_t\}_{t \geq 0}$ satisfying the usual conditions (that is increasing and right continuous, and $\{F_t\}$, $t \geq 0$, contains all P -null sets in F). Throughout this paper let $|\cdot|$ denote the Euclidean vector norm and we shall use the notation.

$$\sup_x |u(x, t)| = \|u(\cdot, t)\| \text{ and } \sup_x |v(x, t)| = \|v(\cdot, t)\|.$$

The L_p – norm of a vector-valued L_p -integrable random variable $Z \in L_p(\Omega, F, P)$ will be denoted by

$$\|Z\|_p = (E \|Z\|_p^p)^{1/p}, 1 \leq p < \infty,$$

where E is the expectation with respect to P .

The Numerical solutions of stochastic delay differential equations or SDDEs are studied in many papers (see [1-10]).

In this paper let $W(t)$ be a n -dimensional Wiener process given on the filtered probability space (Ω, F, P) . We consider the stochastic delay differential equation ($0=t_0 < T < \infty$):

$$\begin{aligned} du(x, t) &= f(x, t, u(x, t), u(x, t-\tau)) dt + g(x, t, u(x, t), u(x, t-\tau)) dW(t), \quad t \in [0, T] \\ u(x, t) &= \Psi(x, t), \quad t \in [-\tau, 0] \end{aligned} \quad (1.1)$$

with fixed lag, where $\Psi(x, t)$ is an F_{t_0} -measurable $C(R^v \times [-\tau, 0], R^n)$ valued random variable such that

$$E \|\Psi\| < \infty.$$

$(C(R^v \times [-\tau, 0], R^n))$ is the Banach space of all continuous paths from $R^v \times [-\tau, 0] \rightarrow R^n$ equipped with the supremum norm

$$\|\eta\|_C = \sup_{t \in [-\tau, 0]} \|\eta(\cdot, t)\|$$

where

$$\|\eta(\cdot, t)\| = \sup_x |\eta(\cdot, t)|.$$

If the functions f and g should not explicitly contain x and t the equation is called autonomous, and we consider this case for simplicity. Equation (1.1) can then be formulated equivalently as

$$u(x, t) = u_0(x) + \int_0^t f(u(x, s), u(x, s-\tau)) ds + \int_0^t g(u(x, s), u(x, s-\tau)) dW(s), \quad (1.2)$$

For $t \in [0, T]$ and with

$$u(x, t) = \Psi(x, t), \text{ for } t \in [-\tau, 0].$$

We have $f : R^{n+v+1} \rightarrow R^n$, $g : R^{n+v+1} \rightarrow R^{n \times n}$ and $\Psi : R^v \times [-\tau, 0] \rightarrow R^n$ and we need the following conditions:

(A1) The functions f and g are continuous

(A2) The functions f and g satisfy a uniform Lipschitz condition; that is there exists positive constants L_1, L_2, L_3 and L_4 such that $\phi_1, \phi_2, \Psi_1, \Psi_2 \in R^n$ and $t \in [0, T]$,

$$\|f(\phi_1, \Psi_1) - f(\phi_2, \Psi_2)\| \leq L_1 \|\phi_1 - \phi_2\| + L_2 \|\Psi_1 - \Psi_2\|, \quad (1.3)$$

and

$$\|g(\phi_1, \Psi_1) - g(\phi_2, \Psi_2)\| \leq L_3 \|\phi_1 - \phi_2\| + L_4 \|\Psi_1 - \Psi_2\|. \quad (1.4)$$

(A3) the function Ψ is Hölder continuous with exponent γ ; that is, such that for $t, s \in [-\tau, 0]$

$$E \|\Psi(\cdot, t) - \Psi(\cdot, s)\|^p \leq L_5 \|t - s\|^{pY}, p = 1, 2 \quad (1.5)$$

(A4) The functions f and g satisfy a linear growth condition; that is, there exist positive constants K_1 and K_2 such that for all $\phi, \phi_1, \Psi, \Psi_1 \in R^n$ and $t \in [0, T]$,

$$\|f(\phi, \phi_1)\|^2 \leq K_1 (1 + \|\phi\|^2 + \|\phi_1\|^2), \quad (1.6)$$

$$\|g(\Psi, \Psi_1)\|^2 \leq K_2 (1 + \|\Psi\|^2 + \|\Psi_1\|^2). \quad (1.7)$$

2. Numerical analysis for an autonomous SDDEs

For simplicity we shall in the sequel consider equation (1.1) in the autonomous form: that is, we shall work with

$$du(x, t) = f(x, t, u(x, t), u(x, t - \tau)) dt + g(x, t, u(x, t), u(x, t - \tau)) dW(t), \quad t \in [0, T]$$

$$u(x, t) = \Psi(x, t), \quad t \in [-\tau, 0]. \quad (2.1)$$

We define a mesh with a uniform step on the interval $[0, T]$, $h = T/N$, $t_n = n.h$, where $n = 0, \dots, N$, and where we assume that for the given h there is a corresponding integer N_τ such that the lag can be expressed in terms of the step size as $\tau = N_\tau.h$. We consider strong approximations $v_n(x)$ of the solution to equation (2.1), using a stochastic explicit one-step method of the form

$$v_{n+1}(x) = v_n(x) + \phi(h, v_n(x), v_{n-N_\tau}(x), I_\phi), n = 0, \dots, N - 1, \quad (2.2)$$

where the initial values are given by

$$v_{n-N_\tau}(x) = \Psi(x, t_n - \tau) \text{ for } n - \tau \leq 0.$$

The increment function $\phi(h, \cdot, \cdot, I_\phi) : R^n \times R^n \rightarrow R^n$ incorporates a finite number of multiple Ito-integrals (see [11]) of the form

$$I_{(j_1, \dots, j_l), h} = \int_t^{t+h} \int_t^{s_1} \dots \int_t^{s_{l-1}} dW^{j_1}(s_1) \dots dW^{j_{l-1}}(s_{l-1}) dW^{j_l}(s_l),$$

Where $j_i \in \{0, 1\}$ and $dW^0(t) = dt$ with $t = t_n$ in the case (2.1). We denote by I_ϕ the collection of Ito-integrals required to compute the increment function ϕ . The increment function ϕ is assumed to generate approximations $v_n(x)$ which are F_{t_n} -measurable. We suppose there exist positive constants C_1, C_2, C_3 such that $\zeta, \zeta^1, \eta - \eta^1 \in R^n$,

$$\|E(\phi(h, \zeta, \eta, I_\phi) - \phi(h, \zeta^1, \eta^1, I_\phi))\| \leq C_1 h (\|\zeta - \zeta^1\| + \|\eta - \eta^1\|), \quad (2.3)$$

$$E(\|\phi(h, \zeta, \eta, I_\phi) - \phi(h, \zeta^1, \eta^1, I_\phi)\|^2) \leq C_2 h (\|\zeta - \zeta^1\|^2 + \|\eta - \eta^1\|^2). \quad (2.4)$$

and

$$E(\|\phi(h, \zeta, \eta, I_\phi)\|^2) \leq C_3 h (1 + \|\zeta\|^2 + \|\eta\|^2). \quad (2.5)$$

Notation 2.1. We denote by $u(x, t_{n+1})$ the value of the exact solution of equation (2.1) at the meshpoint t_{n+1} , by $v_{n+1}(x)$ the value of the approximate solution using equation (2.2), and by $v(x, t_{n+1})$ the value obtained after just one step of equation (2.2): that is,

$$v(x, t_{n+1}) = v(x, t_n) + \phi(h, v(x, t_n), u(x, t_n - \tau), I\phi).$$

Definition 2.1. The error of the above approximation $v_n(x)$ on the meshpoints is the sequence of random variables

$$\epsilon_n := v(x, t_n) - v_n(x), \quad n = 1, \dots, N. \quad (2.6)$$

Note that ϵ_n is F_m -measurable since both $u(x, t_n)$ and $v_n(x)$ are F_m -measurable random variables, and that $(E \|\epsilon_n\|^2)^{1/2}$ is the L^2 -norm of (2.6).

Definition 2.2. Let

$$\delta_{n+1}(x) = u(x, t_{n+1}) - v(x, t_{n+1}), \quad n = 0, \dots, N-1. \quad (2.7)$$

The method (2.2) is said to be consistent with order p_1 in the mean and with order p_2 in the mean-square sense if, with

$$P_2 \geq \frac{1}{2} \text{ and } p_1 \geq p_2 + \frac{1}{2}, \quad (2.8)$$

the estimates

$$\max_{0 \leq n \leq N-1} \|E \|\delta_{n+1}(\cdot)\| ch^{p_2} \text{ as } h \rightarrow 0, \quad (2.9)$$

and

$$\max_{0 \leq n \leq N-1} (E \|\delta_{n+1}(\cdot)\|^2)^{1/2} \leq ch^{p_2} \text{ as } h \rightarrow 0, \quad (2.10)$$

hold, where the (generic) constant C does not depend on h , but may depend on T , and on the initial data. We now state the main theorem of this paper

Theorem 2.1. We assume that the functions f and g satisfy the conditions from A1 to A4. Suppose that the method defined by equation (2.2) is consistent with order p_1 in the mean and order p_2 in the mean-square sense, with p_1 and p_2 satisfying inequality (2.8), and the increment function ϕ in equation (2.2) satisfies the estimates (2.3) and (2.4). Then the approximation (2.2) for equation (2.1) is convergent in L^2 (as $h \rightarrow 0$ with $\tau/h \in N$) with order $p = p_1 - \frac{1}{2}$. That is, convergence is in the mean-square sense, and

$$\max_{1 \leq n \leq N} (E \|\epsilon_n\|^2)^{1/2} \leq ch^p \text{ as } h \rightarrow 0. \quad (2.11)$$

Proof. Using Notation 2.1, adding and subtracting $u(x, t_n)$ and $\phi(h, u(x, t_n), u(x, t_n - \tau), I\phi)$, and rearranging, we obtain

$$\begin{aligned}
 \epsilon_{n+1} &= u(x, t_{n+1}) - v_{n+1}(x) \\
 &= u(x, t_n) - v_n(x) + u(x, t_{n+1}) - u(x, t_n) - \phi(h, u(x, t_n), u(x, t_n - \tau), I_\phi) \\
 &\quad + \phi(h, u(x, t_n), u(x, t_n - \tau), I_\phi) - \phi(h, v_n(x), v_{n-N_\tau}(x), I_\phi) \\
 &= \epsilon_n + \delta_{n+1} + z_n,
 \end{aligned}$$

where

$$\begin{aligned}
 \epsilon_n &= u(x, t_n) - v_n(x), \\
 \delta_{n+1} &= u(x, t_{n+1}) - u(x, t_n) - \phi(h, u(x, t_n), u(x, t_n - \tau), I_\phi)
 \end{aligned}$$

and

$$z_n = \phi(h, u(x, t_n), u(x, t_n - \tau), I_\phi) - \phi(h, v_n(x), v_{n-N_\tau}(x), I_\phi). \quad (2.12)$$

Thus, squaring, employing the conditional means with respect to the σ -algebra F_{t_0} and taking the norm, we obtain

$$\begin{aligned}
 E(\|\epsilon_{n+1}\|^2 | F_{t_0}) &\leq E(\|\epsilon_n\|^2 | F_{t_0}) + E(\|\delta_{n+1}\|^2 | F_{t_0}) + E(\|z_n\|^2 | F_{t_0}) \\
 &\quad + 2\|E(\delta_{n+1} \cdot \epsilon_n | F_{t_0})\| + 2\|E(\delta_{n+1} \cdot z_n | F_{t_0})\| + 2\|E(\epsilon_n \cdot z_n | F_{t_0})\|,
 \end{aligned} \quad (2.13)$$

which holds almost surely.

We shall now estimate the separate terms in inequality (2.13) individually and in sequence; all the estimates hold almost surely. We shall frequently use the Holder inequality, the inequality $2ab \leq a^2 + b^2$ and properties of conditional expectation, which can be found in [12]. In the sequel we shall use c to denote an unspecified constant, which depends only on the constants $L_1, L_2, L_3, L_4, k_1, k_2, c_1$ and c_2 , and on T and the initial data.

Due to the assumed consistency in the mean-square sense of the method, we have

$$E(\|\delta_{n+1}\|^2 | F_{t_0}) = E(E(\|\delta_{n+1}\|^2 | F_{t_n}) | F_{t_0}) \leq ch^{2p_2}.$$

Due to property (2.4) of the increment function, we have

$$E(\|z_n\|^2 | F_{t_0}) \leq chE(\|\epsilon_n\|^2 | F_{t_0}) + chE(\|\epsilon_{n-N_\tau}\|^2 | F_{t_0}).$$

We have, due to the consistency condition,

$$\begin{aligned}
 2\|E(\delta_{n+1} \cdot \epsilon_n | F_{t_0})\| &\leq 2\|E(E(\delta_{n+1} | F_{t_n}) \epsilon_n | F_{t_0})\| \leq 2(E\|E(\delta_{n+1} | F_{t_n})\|^2)^{\frac{1}{2}} \cdot (E\|\epsilon_n\|^2 | F_{t_0})^{\frac{1}{2}} \\
 &= 2(E(ch^{2p_1-1}))^{\frac{1}{2}} \cdot (hE(\|\epsilon_n\|^2 | F_{t_0}))^{\frac{1}{2}} \leq ch^{2p_1-1} + hE(\|\epsilon_n\|^2 | F_{t_0}).
 \end{aligned}$$

By employing the consistency condition and property (2.4) of the increment function ϕ , we have

$$\begin{aligned}
 2\|E(\delta_{n+1} \cdot z_n | F_{t_0})\| &\leq 2(E(\|\delta_{n+1}\|^2 | F_{t_0}))^{\frac{1}{2}} (E(\|z_n\|^2 | F_{t_0}))^{\frac{1}{2}} \\
 &\leq E(E(\|\delta_{n+1}\|^2 | F_{t_n}) | F_{t_0}) + E(\|z_n\|^2 | F_{t_0}) \leq ch^{2p_2} + chE(c_n^2 | F_{t_0}) + chE(c_{n-N_\tau}^2 | F_{t_0}).
 \end{aligned}$$

Using definition (2.12) and property (2.3) of the increment function ϕ , we have

$$\begin{aligned} 2 \| (z_n, \epsilon_n | F_{t_0}) \| &\leq 2E(\| E(z_n | F_{t_n}) \| \cdot \| \epsilon_n \| | F_{t_0}) \leq chE(\| \epsilon_n \|^2 | F_{t_0}) + 2chE(\| \epsilon_n \| \| \epsilon_{n-N\tau} \| | F_{t_0}) \\ &\leq chE(\| \epsilon_n \|^2 | F_{t_0}) + ch[2(E(\| \epsilon_n \|^2 | F_{t_0}))^{\frac{1}{2}} \cdot (E(\| \epsilon_{n-N\tau} \|^2 | F_{t_0}))^{\frac{1}{2}}] \\ &\leq chE(\| \epsilon_n \|^2 | F_{t_0}) + chE(\| \epsilon_n \|^2 | F_{t_0}) + chE(\| \epsilon_{n-N\tau} \|^2 | F_{t_0}) \\ &\leq chE(\| \epsilon_n \|^2 | F_{t_0}) + chE(\| \epsilon_{n-N\tau} \|^2 | F_{t_0}). \end{aligned}$$

Combining these results with $2_{p2} \leq 2_{p1} - 1$, we obtain

$$E(\epsilon_{n+1}^2 | F_{t_0}) \leq (1 + ch)E(\epsilon_n^2 | F_{t_0}) + ch^{2p2} + chE(\| \epsilon_{n-N\tau} \|^2 | F_{t_0}).$$

Now we shall prove the assertion by an induction argument over consecutive intervals of length τ up to the end of the interval $[0, T]$. Since we have exact initial values, we set

$$\epsilon_n = 0 \text{ for } n = -N\tau, \dots, 0.$$

Step 1. Suppose that $t_n \in [0, \tau]$; that is, $n = 1, \dots, N\tau$ and $\epsilon_{n-N\tau} = 0$.

$$\begin{aligned} E(\epsilon_{n+1}^2 | F_{t_0}) &\leq (1 + ch)E(\epsilon_n^2 | F_{t_0}) + ch^{2p2} \leq ch^{2p2} \sum_{k=0}^n (1 + ch)^k \\ &= ch^{2p2} \frac{(1 + ch)^{n+1} - 1}{(1 + ch) - 1} \leq ch^{2p2-1} ((e^{ch})^{n+1} - 1) \leq ch^{2p2-1} (e^{cT} - 1). \end{aligned}$$

Step 2. Suppose that $t_n \in [k\tau, (k+1)\tau]$, and make the assumption that

$$E(\| \epsilon_{n-N\tau} \|^2 | F_{t_0}) \leq ch^{2p2-1}.$$

Then

$$\begin{aligned} E(\epsilon_{n+1}^2 | F_{t_0}) &\leq (1 + ch)E(\epsilon_n^2 | F_{t_0}) + ch^{2p2} + chE(\| \epsilon_{n-N\tau} \|^2 | F_{t_0}) \leq (1 + ch)E(\epsilon_n^2 | F_{t_0}) + ch^{2p2} + hch^{2p2-1} \\ &= (1 + ch)E(\epsilon_n^2 | F_{t_0}) + ch^{2p2} \leq ch^{2p2-1} (e^{cT} - 1), \end{aligned}$$

by the same arguments as above. This, implies, almost surely, that

$$(E(\epsilon_{n+1}^2 | F_{t_0}))^{\frac{1}{2}} \leq ch^{2p2-\frac{1}{2}},$$

which proves the theorem

References

- [1] C.T.H. Baker and E. Buckwar, Numerical analysis of explicit one-step method for stochastic delay differential equations, London Mathematical Society, ISSN 1461- 1570, 2000.
- [2] E. Buckwar and T. Shardlow, Weak approximation of stochastic differential delay equations, 2003, preprint.
- [3] C.T.H. Baker and N. Ford, Convergence of linear multistep methods for a

- class of delay-integro-differential equations, in international series of numerical mathematics, vol. 86, Birkhauser Verlag Basel, 47-59, 1988.
- [4] E. Buckwar and T. Shardlow, weak approximation of stochastic differential delay equations, *IMA. J. Numer. Anal.* 25, 57-86, 2005.
 - [5] Y. Hu, S. E-A.Mohammed and F. Yan, discrete-time approximations of stochastic delay equations: the Milstein scheme, the *Annals of probability*. 32 (1A), 265-314, 2004.
 - [6] X. Mao and S. Sabanis, numerical solutions of stochastic differential delay equations under local Lipschitz condition, *J.Comput. Appl. Math.* 151 (1), 215-227, 2003.
 - [7] U. Kuchler and E. Platen, Strong discrete time approximation of stochastic differential equations with time delay, *Math. Comput. Simulation*, 54, 189-205, 2000.
 - [8] A. Bellen and M. Zennaro, numerical methods for delay differential equations, Oxford University Press, 2003.
 - [9] G.A. Bocharov and F.A. Rihan, numerical modelling in biosciences using delay differential equations, *J. Comput. Appl. Math.*, 125 (1-2), 183-199, 2000.
 - [10] E. Buckwar and R. Winkler, multi-step Maruyama methods for stochastic delay differential equations, Humboldt-Universitat zu Berlin, Institut fur mathematik, preprint 2004-15.
 - [11] P.E. Kloeden and E. Platen, numerical solution of stochastic differential equations, Springer, Berlin, 315-320, 1992.
 - [12] D. Williams, probability with martingales, Cambridge University press, Cambridge, 315, 317, 322, 1991.