

## Series 5

1. (i) See file `Milstein1D.m`  
(ii) See file `Milstein_SDE1.m`.

```
>> Milstein_SDE1  
Strong rate of convergence in L^1: 1.016  
Strong rate of convergence in L^2: 1.0051
```

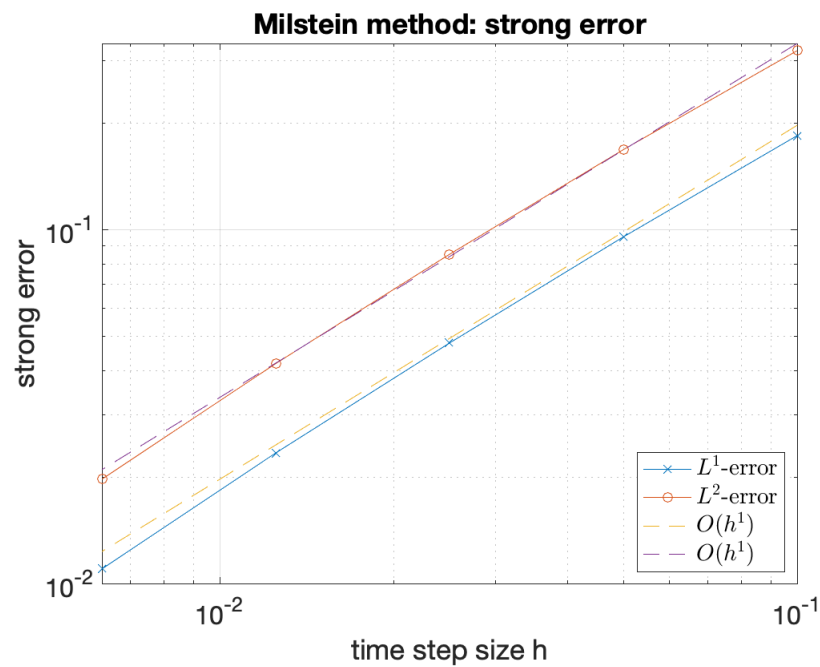


Abbildung 1: Since all assumptions of Theorem 3.6.5 are satisfied, we see strong convergence of order one in both the  $L^1$ - and the  $L^2$ -norm.

(iii) See file `Milstein_SDE2.m`.

```
>> Milstein_SDE2
Strong rate of convergence in L^1: 0.87553
Strong rate of convergence in L^2: 0.60607
```

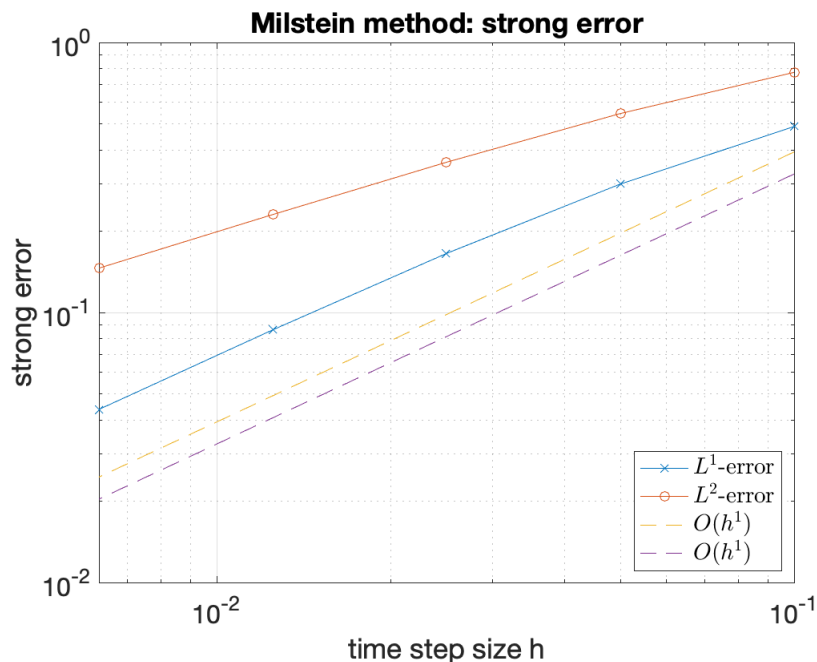


Abbildung 2: We do not recover convergence of order one for the strong error, but we observe a slower decay of roughly  $\mathcal{O}(\Delta t^{0.88})$  for the  $L^1$ -error and of  $\mathcal{O}(\Delta t^{0.61})$  for the  $L^2$ -error. This is due to the fact that the diffusion coefficient  $\sigma$  has an unbounded derivative  $\sigma'(x) = 2x \cos(1 + x^2)$ .

2. (i) We keep the notation as in the lecture slides and define the mappings

$$\mu: \mathbb{R} \rightarrow \mathbb{R}, \quad x \mapsto a(b - x)$$

and

$$\sigma: \mathbb{R} \rightarrow \mathbb{R}, \quad x \mapsto \sigma_v \sqrt{|x|}.$$

In order to show the uniqueness of the solution process  $V: [0, T] \times \Omega \rightarrow \mathbb{R}$ , we prove that the conditions of the Yamada-Watanabe theorem are satisfied (for the case  $d = m = 1$ ). We start showing that the mapping  $\mu: [0, T] \times \mathbb{R} \rightarrow \mathbb{R}$  satisfies condition (2) with  $\kappa: [0, +\infty) \rightarrow [0, +\infty)$  given by

$$\kappa(x) = ax, \quad x \in \mathbb{R}.$$

Indeed, we have that for every  $t \in [0, T]$  and for every  $x, y \in \mathbb{R}$

$$|a(b - x) - a(b - y)| = a|b - x - b + y| = a|x - y| = \kappa(|x - y|).$$

Moreover, the mapping  $\sigma: [0, T] \times \mathbb{R} \rightarrow \mathbb{R}$  satisfies condition (2) with  $\varrho: [0, +\infty) \rightarrow [0, +\infty)$  given by

$$\varrho(x) = \sigma_v \sqrt{|x|}, \quad x \in \mathbb{R}.$$

Precisely, we have that for every  $t \in [0, T]$  and for every  $x, y \in \mathbb{R}$

$$\begin{aligned} |\sigma_v \sqrt{|x|} - \sigma_v \sqrt{|y|}| &= \sigma_v |\sqrt{|x|} - \sqrt{|y|}| = \sigma_v \frac{||x| - |y||}{\sqrt{|x|} + \sqrt{|y|}} = \sigma_v \sqrt{||x| - |y||} \frac{\sqrt{||x| - |y||}}{\sqrt{|x|} + \sqrt{|y|}} \\ &\leq \sigma_v \sqrt{|x - y|} = \varrho(|x - y|), \end{aligned}$$

where the last inequality follows by the trivial inequality  $\sqrt{||x| - |y||} / \sqrt{|x|} + \sqrt{|y|} \leq 1$ . Now, since  $d = m = 1$ , we can conclude the exercise showing that conditions (3') and (4') are satisfied. The function  $\kappa(x) = ax$  is concave and satisfies condition (3'). Finally, for every  $\gamma > 0$  we have that

$$\int_0^\gamma \kappa(z)^{-1} dz = a \int_0^\gamma \frac{1}{z} dz = +\infty, \quad \int_0^\gamma \varrho(z)^{-2} dz = \sigma_v \int_0^\gamma \frac{1}{z} dz = +\infty,$$

which shows that condition (4') is also satisfied. Therefore, we can apply the Yamada-Watanabe theorem to conclude that the Cox-Ingersoll-Ross process is the unique (up to indistinguishability) solution to the SDE

$$dV_t = a(b - V_t)dt + \sigma_v \sqrt{V_t} dW_t, \quad t \in [0, T], \quad V_0 = v_0.$$

- (ii) The drift-implicit Milstein scheme of the stochastic process  $V$  with stepsize  $\Delta t = T/N$  and initial value  $V_0^N = V_0 > 0$  is given for  $n = 0, \dots, N-1$  by

$$V_{n+1}^N = V_n^N + a(b - V_{n+1}^N)\Delta t + \sigma_v \sqrt{V_n^N} (W_{t_{n+1}} - W_{t_n}) + \frac{\sigma_v^2}{4} ((W_{t_{n+1}} - W_{t_n})^2 - \Delta t). \quad (1)$$

Denoting the increments of  $W$  by  $\Delta W_n := W_{t_{n+1}} - W_{t_n}$  for  $n = 0, \dots, N-1$  and resolving equation (1) for  $V_{n+1}^N$  yields

$$\begin{aligned} V_{n+1}^N &= \frac{1}{1 + a\Delta t} \left( V_n^N + ab\Delta t + \sigma_v \sqrt{V_n^N} \Delta W_n + \frac{\sigma_v^2}{4} ((\Delta W_n)^2 - \Delta t) \right) \\ &= \frac{1}{1 + a\Delta t} \left( V_n^N + \left( ab - \frac{\sigma_v^2}{4} \right) \Delta t + \sigma_v \sqrt{V_n^N} \Delta W_n + \frac{\sigma_v^2}{4} (\Delta W_n)^2 \right) \\ &\geq \frac{1}{1 + a\Delta t} \left( V_n^N + \sigma_v \sqrt{V_n^N} \Delta W_n + \frac{\sigma_v^2}{4} (\Delta W_n)^2 \right) \\ &= \frac{1}{1 + a\Delta t} \left( \sqrt{V_n^N} + \frac{\sigma_v}{2} \Delta W_n \right)^2, \end{aligned}$$

where in the third step we have used the hypothesis  $4ab \geq \sigma_v^2$ . Since  $V_0^N = V_0 > 0$  and  $P(\sigma_v \Delta W_0 / 2 = -\sqrt{V_0}) = 0$ , we have that  $P(V_1^N > 0) = 1$ . Hence, by induction it follows that  $P(V_n^N > 0) = 1$  for all  $n = 0, \dots, N$ .

- (iii) See the files `DriftImplicitMilstein.m` and `DriftImplicitMilsteinPlot.m`.

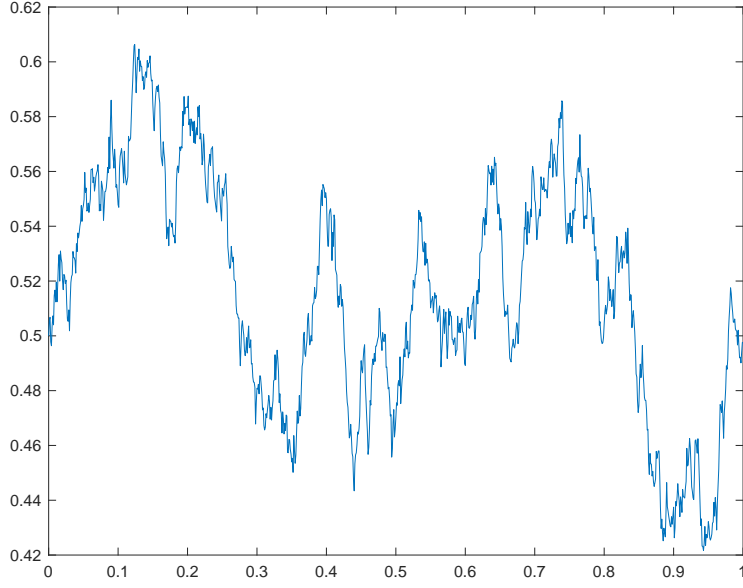


Abbildung 3: By item (ii) we know that  $P(V_n^N > 0) = 1$  for all  $n \in \{0, \dots, N\}$  whenever the parameters  $a, b, \sigma_v$  satisfy  $4ab \geq \sigma_v^2$ . The condition  $4ab \geq \sigma_v^2$  is fulfilled by the choice of the parameters  $a = 2, b = 0.5$  and  $\sigma_v = 0.25$ . The expected behaviour of the drift-implicit Milstein approximation is realized in the experiment.

**3. Proof of Proposition 3.6.6.** We start computing the iterated integrals (4) given in the hint. Let  $(W^{(1)}, W^{(2)}): [0, T] \times \Omega \rightarrow \mathbb{R}^2$  be a 2-dimensional standard Brownian motion.

The Itô's formula applied to  $W^{(1)}: [0, T] \times \Omega \rightarrow \mathbb{R}$  and to the function  $\mathbb{R} \ni x \mapsto x^2$ , yields

$$(W_t^{(1)})^2 = (W_{t_0}^{(1)})^2 + 2 \int_{t_0}^t W_s^{(1)} dW_s^{(1)} + t - t_0. \quad (2)$$

Furthermore, we may compute the second expression in (4) by applying the multi-dimensional Itô formula to  $(W^{(1)}, W^{(2)}): [0, T] \times \Omega \rightarrow \mathbb{R}^2$  together with the function  $\mathbb{R} \ni (x, y) \mapsto xy$ , i.e.

$$W_t^{(1)} W_t^{(2)} = W_{t_0}^{(1)} W_{t_0}^{(2)} + \int_{t_0}^t W_s^{(1)} dW_s^{(2)} + \int_{t_0}^t W_s^{(2)} dW_s^{(1)}. \quad (3)$$

We are now ready to prove Proposition 3.6.6. By the commutative noise assumption,

we have that for all  $n \in \{0, 1, \dots, N-1\}$  it holds  $P$ -a.s. that

$$\begin{aligned}
& \sum_{i,j=1}^m (\sigma_i)'(Y_n^N) \sigma_j(Y_n^N) \int_{t_n}^{t_{n+1}} \int_{t_n}^s dW_u^{(j)} dW_s^{(i)} \\
&= \sum_{i=1}^m (\sigma_i)'(Y_n^N) \sigma_i(Y_n^N) \int_{t_n}^{t_{n+1}} \int_{t_n}^s dW_u^{(i)} dW_s^{(i)} \\
&\quad + \frac{1}{2} \sum_{\substack{i,j=1 \\ i \neq j}}^m \left( (\sigma_i)'(Y_n^N) \sigma_j(Y_n^N) \int_{t_n}^{t_{n+1}} \int_{t_n}^s dW_u^{(j)} dW_s^{(i)} \right. \\
&\quad \left. + (\sigma_j)'(Y_n^N) \sigma_i(Y_n^N) \int_{t_n}^{t_{n+1}} \int_{t_n}^s dW_u^{(i)} dW_s^{(j)} \right) \\
&= \sum_{i=1}^m (\sigma_i)'(Y_n^N) \sigma_i(Y_n^N) \int_{t_n}^{t_{n+1}} \int_{t_n}^s dW_u^{(i)} dW_s^{(i)} \tag{4} \\
&\quad + \frac{1}{2} \sum_{\substack{i,j=1 \\ i \neq j}}^m (\sigma_i)'(Y_n^N) \sigma_j(Y_n^N) \left( \int_{t_n}^{t_{n+1}} \int_{t_n}^s dW_u^{(j)} dW_s^{(i)} + \int_{t_n}^{t_{n+1}} \int_{t_n}^s dW_u^{(i)} dW_s^{(j)} \right).
\end{aligned}$$

We apply Equation (2) to compute the iterated integral in (4)

$$\begin{aligned}
& \int_{t_n}^{t_{n+1}} \int_{t_n}^s dW_u^{(i)} dW_s^{(i)} = \int_{t_n}^{t_{n+1}} \int_0^s dW_u^{(i)} dW_s^{(i)} - \int_{t_n}^{t_{n+1}} \int_0^{t_n} dW_u^{(i)} dW_s^{(i)} \\
&= \int_{t_n}^{t_{n+1}} W_s^{(i)} dW_s^{(i)} - \int_{t_n}^{t_{n+1}} \int_0^{t_n} dW_u^{(i)} dW_s^{(i)} \\
&= \frac{(W_{t_{n+1}}^{(i)})^2 - (W_{t_n}^{(i)})^2 - \Delta t}{2} - W_{t_n}^{(i)} (W_{t_{n+1}}^{(i)} - W_{t_n}^{(i)}) \\
&= \frac{1}{2} (W_{t_{n+1}}^{(i)} - W_{t_n}^{(i)})^2 - \frac{\Delta t}{2}. \tag{5}
\end{aligned}$$

By (5) we have that

$$\begin{aligned}
& \sum_{i,j=1}^m (\sigma_i)'(Y_n^N) \sigma_j(Y_n^N) \int_{t_n}^{t_{n+1}} \int_{t_n}^s dW_u^{(j)} dW_s^{(i)} = \\
&= \frac{1}{2} \sum_{i=1}^m (\sigma_i)'(Y_n^N) \sigma_i(Y_n^N) \left( (W_{t_{n+1}}^{(i)} - W_{t_n}^{(i)})^2 - \Delta t \right) \\
&\quad + \frac{1}{2} \sum_{\substack{i,j=1 \\ i \neq j}}^m (\sigma_i)'(Y_n^N) \sigma_j(Y_n^N) \left( \int_{t_n}^{t_{n+1}} \int_{t_n}^s dW_u^{(j)} dW_s^{(i)} + \int_{t_n}^{t_{n+1}} \int_{t_n}^s dW_u^{(i)} dW_s^{(j)} \right). \tag{6}
\end{aligned}$$

Then, we exploit Equation (3) to compute the iterated integrals in (6) and we obtain

$$\begin{aligned}
& \int_{t_n}^{t_{n+1}} \int_{t_n}^s dW_u^{(j)} dW_s^{(i)} + \int_{t_n}^{t_{n+1}} \int_{t_n}^s dW_u^{(i)} dW_s^{(j)} \\
&= \int_{t_n}^{t_{n+1}} W_s^{(j)} dW_s^{(i)} - W_{t_n}^{(j)} (W_{t_{n+1}}^{(i)} - W_{t_n}^{(i)}) \\
&\quad + \int_{t_n}^{t_{n+1}} W_s^{(i)} dW_s^{(j)} - W_{t_n}^{(i)} (W_{t_{n+1}}^{(j)} - W_{t_n}^{(j)}) \\
&= W_{t_{n+1}}^{(i)} W_{t_{n+1}}^{(j)} - W_{t_n}^{(i)} W_{t_n}^{(j)} + 2W_{t_n}^{(i)} W_{t_n}^{(j)} - W_{t_n}^{(j)} W_{t_{n+1}}^{(i)} - W_{t_n}^{(i)} W_{t_{n+1}}^{(j)} \\
&= (W_{t_{n+1}}^{(i)} - W_{t_n}^{(i)}) (W_{t_{n+1}}^{(j)} - W_{t_n}^{(j)}).
\end{aligned}$$

Therefore, we obtain the desired result

$$\begin{aligned}
& \sum_{i,j=1}^m (\sigma_i)'(Y_n^N) \sigma_j(Y_n^N) \int_{t_n}^{t_{n+1}} \int_{t_n}^s dW_u^{(j)} dW_s^{(i)} \\
&= \frac{1}{2} \sum_{i=1}^m (\sigma_i)'(Y_n^N) \sigma_i(Y_n^N) \left( (W_{t_{n+1}}^{(i)} - W_{t_n}^{(i)})^2 - \frac{T}{N} \right) \\
&\quad + \frac{1}{2} \sum_{\substack{i,j=1 \\ i \neq j}}^m (\sigma_i)'(Y_n^N) \sigma_j(Y_n^N) (W_{t_{n+1}}^{(i)} - W_{t_n}^{(i)}) (W_{t_{n+1}}^{(j)} - W_{t_n}^{(j)}) \\
&= \frac{1}{2} \sum_{i,j=1}^m (\sigma_i)'(Y_n^N) \sigma_j(Y_n^N) (W_{t_{n+1}}^{(i)} - W_{t_n}^{(i)}) (W_{t_{n+1}}^{(j)} - W_{t_n}^{(j)}) \\
&\quad - \frac{\Delta t}{2} \sum_{i=1}^m (\sigma_i)'(Y_n^N) \sigma_i(Y_n^N).
\end{aligned}$$

□

**Webpage:** <https://moodle-app2.let.ethz.ch/course/view.php?id=17423>

**Organisation:** Francesca Bartolucci, HG G 53.2