Stochastic Simulations for DREAM4

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ODE model (DREAM3) 1

$$\frac{dx_i}{dt} = F_i^{RNA}(\boldsymbol{x}, \boldsymbol{y}) = m_i \cdot f_i(\boldsymbol{y}) - \lambda_i^{RNA} \cdot x_i$$
 (1)

$$\frac{dx_i}{dt} = F_i^{RNA}(\boldsymbol{x}, \boldsymbol{y}) = m_i \cdot f_i(\boldsymbol{y}) - \lambda_i^{RNA} \cdot x_i \qquad (1)$$

$$\frac{dy_i}{dt} = F_i^{Prot}(\boldsymbol{x}, \boldsymbol{y}) = r_i \cdot x_i - \lambda_i^{Prot} \cdot y_i \qquad (2)$$

where m_i is the maximum transcription rate, r_i the translation rate, λ_i^{RNA} and λ_i^{Prot} are the mRNA and protein degradation rates, and $f_i(\cdot)$ is the so-called input function of gene i. The input function computes the relative activation of the gene, which is between 0 (the gene is shut off) and 1 (the gene is maximally activated), given the transcription-factor (TF) concentrations y.

$\mathbf{2}$ SDE model (DREAM4)

$$\frac{dx_i}{dt} = F_i^{RNA}(\boldsymbol{x}, \boldsymbol{y}) + \sigma_i^{RNA} \cdot \eta_i \qquad (3)$$

$$\frac{dy_i}{dt} = F_i^{Prot}(\boldsymbol{x}, \boldsymbol{y}) + \sigma_i^{Prot} \cdot \zeta_i \qquad (4)$$

$$\frac{dy_i}{dt} = F_i^{Prot}(\boldsymbol{x}, \boldsymbol{y}) + \sigma_i^{Prot} \cdot \zeta_i \tag{4}$$

where each η_i and ζ_i is an independent Gaussian white noise with zero mean and unit variance. σ_i^{RNA} and σ_i^{Prot} represent the amplitude (standard deviation) of the noise.

3 Numerical simulation of SDEs

For notational simplicity, we consider here only a single equation and not a system of equations. Equations (3) and (4) are of the following, general form (note that we use the Stratonovich scheme)

$$dX_t = F(X_t)dt + G(X_t)dW_t (5)$$

$$dX_t = F(X_t)dt + G(X_t) \circ dW_t \tag{6}$$

$$\underline{F} = F - \frac{1}{2}G'G \tag{7}$$

where dW_t is a Wiener process. The Itô scheme is defined by (5) and the equivalent Stratonovich scheme is given by (6) and (7).^{1,5} In (3) and (4) the amplitude of the noise $G(X_t)$ is a constant σ_i .

We propose to use the Milstein scheme for the numerical integration, which is better than the basic Euler-Marumaya method, but still easy to implement. 1,3,5,6 Given $X(n) = X_n$, the value at the next discrete time point X_{n+h} is approximated by

$$X_{n+h} = X_n + \underline{F}(X_n)h + G(X_n)\Delta W_n + \frac{1}{2}G'(X_n)G(X_n)[\Delta W_n]^2$$
 (8)

$$\Delta W_n = [W_{t+h} - W_t] \sim \sqrt{h} \mathcal{N}(0, 1) \tag{9}$$

where h is the step size.

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