

Noise propagation in gene regulation networks involving interlinked positive and negative feedback loops

(Supplementary Text S1)

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1 Signal sensitivity and noise amplification

To study the propagation of the input signal involving noise, we define the steady-state sensitivity susceptibility S to measure the change in the output signal due to the input change [1-3],

$$S_\phi = \frac{\langle \alpha \rangle d\langle \phi \rangle}{\langle \phi \rangle d\langle \alpha \rangle} = \frac{d\ln\langle \phi \rangle}{d\ln\langle \alpha \rangle} \quad (1)$$

$$S_\mu = \frac{\langle \alpha \rangle d\langle \mu \rangle}{\langle \mu \rangle d\langle \alpha \rangle} = \frac{d\ln\langle \mu \rangle}{d\ln\langle \alpha \rangle}. \quad (2)$$

Here S_ϕ and S_μ represent the relative change of protein and miRNAs following the change in the input signal, respectively. $\langle \dots \rangle$ means the parameters are measured at the stable state.

The abstract dynamics of the protein-miRNAs network is the following [4, 5]

$$\varepsilon \frac{d\phi}{dt} = \alpha + \left(\frac{\kappa\phi^2}{\gamma_1 + \phi^2 + \gamma_2\mu} \right) - \phi \quad (3)$$

$$\frac{d\mu}{dt} = 1 + \phi - \mu. \quad (4)$$

To briefly describe, Eqs. (3-4) are explicitly rewritten by

$$\frac{d\phi}{dt} = J_1^+(\alpha, \phi, \mu) - J_1^-(\alpha, \phi, \mu) \quad (5)$$

$$\frac{d\mu}{dt} = J_2^+(\phi, \mu) - J_2^-(\phi, \mu), \quad (6)$$

where J_1^+ and J_1^- (J_2^+ and J_2^-) are the total fluxes of production and elimination of protein (miRNAs), respectively. Comparing with Eqs. (3) and (4), we have

$$J_1^+ = \frac{1}{\varepsilon} \left(\alpha + \left(\frac{\kappa\phi^2}{\gamma_1 + \phi^2 + \gamma_2\mu} \right) \right) \quad (7)$$

$$J_1^- = \frac{1}{\varepsilon} \phi \quad (8)$$

$$J_2^+ = 1 + \phi \quad (9)$$

$$J_2^- = \mu. \quad (10)$$

When the system locates in a stable steady state, the protein and miRNAs are not changed with time. So Eqs. (5) and (6) are equal to zero. It means

$$\langle J_1^+ \rangle = \langle J_1^- \rangle = \langle J_1 \rangle \quad (11)$$

$$\langle J_2^+ \rangle = \langle J_2^- \rangle = \langle J_2 \rangle. \quad (12)$$

Based on frequency domain analysis [6-8], we differentiate Eqs. (5) and (6) with respect to α at the steady state by using the chain rule, and then multiply with $\langle \alpha \rangle / \langle J_1 \rangle$ and $\langle \alpha \rangle / \langle J_2 \rangle$, respectively,

$$\frac{\langle \alpha \rangle}{\langle J_1 \rangle} \left[\frac{\partial (\langle J_1^+ \rangle - \langle J_1^- \rangle)}{\partial \langle \alpha \rangle} + \frac{\partial (\langle J_1^+ \rangle - \langle J_1^- \rangle)}{\partial \langle \phi \rangle} \frac{d\langle \phi \rangle}{d\langle \alpha \rangle} + \frac{\partial (\langle J_1^+ \rangle - \langle J_1^- \rangle)}{\partial \langle \mu \rangle} \frac{d\langle \mu \rangle}{d\langle \alpha \rangle} \right] = 0 \quad (13)$$

$$\frac{\langle \alpha \rangle}{\langle J_2 \rangle} \left[\frac{\partial (\langle J_2^+ \rangle - \langle J_2^- \rangle)}{\partial \langle \alpha \rangle} + \frac{\partial (\langle J_2^+ \rangle - \langle J_2^- \rangle)}{\partial \langle \phi \rangle} \frac{d\langle \phi \rangle}{d\langle \alpha \rangle} + \frac{\partial (\langle J_2^+ \rangle - \langle J_2^- \rangle)}{\partial \langle \mu \rangle} \frac{d\langle \mu \rangle}{d\langle \alpha \rangle} \right] = 0. \quad (14)$$

Considering the definition of the reaction flux elasticities H_{ij} [1, 2], it should be

$$H_{ij} = -\frac{\langle n_i \rangle}{\langle J_j \rangle} \left(\frac{\partial \langle J_i^+ \rangle}{\partial \langle n_j \rangle} - \frac{\partial \langle J_i^- \rangle}{\partial \langle n_j \rangle} \right) = -\frac{\langle n_j \rangle}{\langle J_j \rangle} A_{ij}, \quad (15)$$

where we use n_0, n_1, n_2 in substitution of α, ϕ, μ , and $A_{ij} = \frac{\partial}{\partial \langle n_j \rangle} \frac{\partial \langle n_i \rangle}{\partial t}$ with $i = 1, 2$ and $j = 0, 1, 2$.

Finally, Eqs. (13) and (14) are rewritten by

$$H_{10} + H_{11}S_1 + H_{12}S_2 = 0 \quad (16)$$

$$H_{20} + H_{21}S_1 + H_{22}S_2 = 0, \quad (17)$$

where S_ϕ and S_μ are replaced by S_1 and S_2 to represent the susceptibility of the protein and the miRNAs, respectively. H_{ij} are

$$H_{10} = -\frac{\langle \alpha \rangle}{\langle \phi \rangle} \quad (18)$$

$$H_{11} = 1 - \frac{2\kappa\langle \phi \rangle(\gamma_1 + \gamma_2\langle \mu \rangle)}{(\gamma_1 + \langle \phi \rangle)^2 + \gamma_2\langle \mu \rangle^2} \quad (19)$$

$$H_{12} = -\frac{\gamma_2\kappa\langle \phi \rangle\langle \mu \rangle}{(\gamma_1 + \langle \phi \rangle)^2 + \gamma_2\langle \mu \rangle^2} \quad (20)$$

$$H_{20} = 0 \quad (21)$$

$$H_{21} = -\frac{\langle \phi \rangle}{\langle \mu \rangle} \quad (22)$$

$$H_{22} = 1. \quad (23)$$

Here, note that all quantities are measured at the steady state.

From Eqs. (16) and (17), the noise susceptibilities of the protein and miRNAs are,

$$S_\phi = S_1 = \left| \frac{H_{20}H_{12} - H_{10}H_{22}}{H_{11}H_{22} - H_{21}H_{12}} \right| \quad (24)$$

$$S_\mu = S_2 = \left| \frac{H_{10}H_{21} - H_{11}H_{20}}{H_{11}H_{22} - H_{12}H_{21}} \right|. \quad (25)$$

Here, $S_\phi < 1$ ($S_\mu < 1$) means the signal sensitivity is relatively low or the changes of protein (miRNAs) module is less than that of input signal. On the contrary, $S_\phi > 1$ ($S_\mu > 1$) means a higher signal sensitivity and the changes of protein (miRNAs) module is larger than that of input signal. Clearly, a larger value of S_ϕ and S_μ is of great benefit to biological networks.

To obtain the noise propagation from the input signal to the output, there is another measurement, the noise amplification A , that is defined as the ratio between the output noise and input [6]

$$A_\phi = \frac{\eta_\phi}{\eta_\alpha} = \frac{std(\phi)/\langle \phi \rangle}{std(\alpha)/\langle \alpha \rangle} \quad (26)$$

$$A_\mu = \frac{\eta_\mu}{\eta_\alpha} = \frac{std(\mu)/\langle \mu \rangle}{std(\alpha)/\langle \alpha \rangle}, \quad (27)$$

where A_ϕ and A_μ denote the noise amplification of protein and miRNAs due to the fluctuation in the input signal, respectively. std and η represent the standard deviation and the relative standard deviation, respectively. Clearly, for $A_\phi > 1$ ($A_\mu > 1$), the noise involved in ϕ (μ) is propagated and amplified, vice versa.

Similarly, using the approach of frequency domain analysis [7, 9], in terms of steady state fluctuations $\Delta n_0 = n_0(t) - \langle n_0 \rangle$, $\Delta n_1 = n_1(t) - \langle n_1 \rangle$, $\Delta n_2 = n_2(t) - \langle n_2 \rangle$, we rewrite Eqs. (5) and (6) with

$$\frac{d\Delta n_1(t)}{dt} = \frac{\partial(\langle J_1^+ \rangle - \langle J_1^- \rangle)}{\partial \langle n_0 \rangle} \Delta n_0 + \frac{\partial(\langle J_1^+ \rangle - \langle J_1^- \rangle)}{\partial \langle n_1 \rangle} \Delta n_1 + \frac{\partial(\langle J_1^+ \rangle - \langle J_1^- \rangle)}{\partial \langle n_2 \rangle} \Delta n_2 \quad (28)$$

$$\frac{d\Delta n_2(t)}{dt} = \frac{\partial(\langle J_2^+ \rangle - \langle J_2^- \rangle)}{\partial \langle n_0 \rangle} \Delta n_0 + \frac{\partial(\langle J_2^+ \rangle - \langle J_2^- \rangle)}{\partial \langle n_1 \rangle} \Delta n_1 + \frac{\partial(\langle J_2^+ \rangle - \langle J_2^- \rangle)}{\partial \langle n_2 \rangle} \Delta n_2. \quad (29)$$

And then dividing the above equations by J_1 and J_2 respectively, one obtains

$$\frac{\langle n_1 \rangle}{\langle J_1 \rangle} \frac{dx_1}{dt} = \frac{\langle n_0 \rangle}{\langle J_1 \rangle} \frac{\partial(\langle J_1^+ \rangle - \langle J_1^- \rangle)}{\partial \langle n_0 \rangle} x_0 + \frac{\langle n_1 \rangle}{\langle J_1 \rangle} \frac{\partial(\langle J_1^+ \rangle - \langle J_1^- \rangle)}{\partial \langle n_1 \rangle} x_1 + \frac{\langle n_2 \rangle}{\langle J_1 \rangle} \frac{\partial(\langle J_1^+ \rangle - \langle J_1^- \rangle)}{\partial \langle n_2 \rangle} x_2 \quad (30)$$

$$\frac{\langle n_2 \rangle}{\langle J_2 \rangle} \frac{dx_2}{dt} = \frac{\langle n_0 \rangle}{\langle J_2 \rangle} \frac{\partial(\langle J_2^+ \rangle - \langle J_2^- \rangle)}{\partial \langle n_0 \rangle} x_0 + \frac{\langle n_1 \rangle}{\langle J_2 \rangle} \frac{\partial(\langle J_2^+ \rangle - \langle J_2^- \rangle)}{\partial \langle n_1 \rangle} x_1 + \frac{\langle n_2 \rangle}{\langle J_2 \rangle} \frac{\partial(\langle J_2^+ \rangle - \langle J_2^- \rangle)}{\partial \langle n_2 \rangle} x_2, \quad (31)$$

where $x_0(t) = (n_0(t) - \langle n_0 \rangle) / \langle n_0 \rangle$, $x_1(t) = (n_1(t) - \langle n_1 \rangle) / \langle n_1 \rangle$, and $x_2(t) = (n_2(t) - \langle n_2 \rangle) / \langle n_2 \rangle$. According to Eqs. (14-23), we rewrite the above equations with

$$-\tau_1 \frac{dx_1}{dt} = H_{10}x_0 + H_{11}x_1 + H_{12}x_2 \quad (32)$$

$$-\tau_2 \frac{dx_2}{dt} = H_{20}x_0 + H_{21}x_1 + H_{22}x_2, \quad (33)$$

where $\tau_1 = \langle n_1 \rangle / J_1$ and $\tau_2 = \langle n_2 \rangle / J_2$.

To transform the time domain to the frequency domain, we perform the Fourier transformations on Eqs. (32) and (33), $\hat{x}_1(\omega) = \int_{-\infty}^{\infty} x_1(t)e^{-i\omega t} dt$ and $\hat{x}_2(\omega) = \int_{-\infty}^{\infty} x_2(t)e^{-i\omega t} dt$. One obtains the following relations,

$$\hat{x}_1(\omega) = \frac{H_{10}(H_{22} + i\omega\tau_2) - H_{20}H_{12}}{H_{21}H_{12} - (H_{11} + i\omega\tau_1)(H_{22} + i\omega\tau_2)} \hat{x}_0(\omega) \quad (34)$$

$$\hat{x}_2(\omega) = \frac{H_{20}(H_{11} + i\omega\tau_1) - H_{10}H_{21}}{H_{21}H_{12} - (H_{11} + i\omega\tau_1)(H_{22} + i\omega\tau_2)} \hat{x}_0(\omega). \quad (35)$$

Here, $\hat{x}_0(\omega)$ presents a connection between the frequency response x_1 and x_2 , and that of the input signal.

Due to the input fluctuation: $\langle \xi(t)\xi(t+t') \rangle = \langle \alpha \rangle^2 \eta_0^2 e^{-t'/\tau_0}$, we get the correlation function of $x_0(t)$, with magnitude η_0^2

$$\langle x_0(t)x_0(t+t') \rangle = \eta_0^2 e^{-t'/\tau_0}. \quad (36)$$

Therefore, the Fourier transformation for Eq. (36) is

$$\langle \hat{x}_0(\omega)\hat{x}_0^*(\omega) \rangle = 2\eta_0^2 \frac{\tau_0}{\tau_0^2 \omega^2 + 1}, \quad (37)$$

where $\hat{x}_0^*(\omega)$ denotes the complex conjugate. Combining it with Eq. (34) and (35), we obtain the power spectrums of x_1 and x_2 ,

$$\langle \hat{x}_1(\omega)\hat{x}_1^*(\omega) \rangle = \frac{(H_{10}H_{22} - H_{20}H_{12})^2 + \omega^2 H_{10}^2 \tau_2^2}{(H_{21}H_{12} - H_{11}H_{22} + \omega^2 \tau_1 \tau_2)^2 + \omega^2 (\tau_1 H_{22} + \tau_2 H_{11})^2} \langle \hat{x}_0(\omega)\hat{x}_0^*(\omega) \rangle \quad (38)$$

$$\langle \hat{x}_2(\omega)\hat{x}_2^*(\omega) \rangle = \frac{(H_{20}H_{11} - H_{10}H_{21})^2 + \omega^2 H_{20}^2 \tau_1^2}{(H_{21}H_{12} - H_{11}H_{22} + \omega^2 \tau_1 \tau_2)^2 + \omega^2 (\tau_1 H_{22} + \tau_2 H_{11})^2} \langle \hat{x}_0(\omega)\hat{x}_0^*(\omega) \rangle. \quad (39)$$

Now, in order to obtain the noise magnitude η_1 and η_2 , we transform the above equations back to the time domain and replace $t' = 0$ in the autocorrelation function,

$$\eta_1^2 = \frac{1}{2\pi} \int_{-\infty}^{\infty} \langle \hat{x}_1(\omega)\hat{x}_1^*(\omega) \rangle e^{i\omega t'} d\omega \Big|_{t'=0} = \frac{1}{2\pi} \int_{-\infty}^{\infty} \langle \hat{x}_1(\omega)\hat{x}_1^*(\omega) \rangle d\omega \quad (40)$$

$$\eta_2^2 = \frac{1}{2\pi} \int_{-\infty}^{\infty} \langle \hat{x}_2(\omega)\hat{x}_2^*(\omega) \rangle e^{i\omega t'} d\omega \Big|_{t'=0} = \frac{1}{2\pi} \int_{-\infty}^{\infty} \langle \hat{x}_2(\omega)\hat{x}_2^*(\omega) \rangle d\omega. \quad (41)$$

Substituting Eqs. (40-41) into Eqs. (26-27), we get the noise amplifications of A_ϕ and A_μ ,

$$\begin{aligned}
A_\phi &= \left[i\tau_0 \left(\frac{\sqrt{2}[2(H_{10}H_{22}\tau_1\tau_2)^2 - bH_{10}^2]}{c(\tau_1H_{22} + \tau_2H_{11})\sqrt{-b}/\tau_1\tau_2} + \frac{\sqrt{2}[-2(H_{10}H_{22}\tau_1\tau_2)^2 + dH_{10}^2]}{e(\tau_1H_{22} + \tau_2H_{11})e\sqrt{-d}\tau_1\tau_2} \right) \right. \\
&\quad \left. + \frac{\tau_0^2[-H_{10}^2 + (H_{10}H_{22})^2\tau_0^2]}{(\tau_1\tau_2)^2 - [b + a(\tau_1H_{22} + \tau_2H_{11})]\tau_0^2 + (H_{21}H_{12} - H_{11}H_{22})^2\tau_0^4} \right]^{1/2} \\
A_\mu &= \left[i\tau_0 \left(\frac{2\sqrt{2}(-H_{10}H_{21}\tau_1\tau_2)^2}{c(\tau_1H_{22} + \tau_2H_{11})\sqrt{-b}/\tau_1\tau_2} + \frac{-2\sqrt{2}(-H_{10}H_{21}\tau_1\tau_2)^2}{e(\tau_1H_{22} + \tau_2H_{11})e\sqrt{-d}\tau_1\tau_2} \right) \right. \\
&\quad \left. + \frac{(H_{20}H_{11} - H_{10}H_{21})^2\tau_0^4}{(\tau_1\tau_2)^2 - [b + a(\tau_1H_{22} + \tau_2H_{11})]\tau_0^2 + (H_{21}H_{12} - H_{11}H_{22})^2\tau_0^4} \right]^{1/2}, \tag{42}
\end{aligned}$$

where the parameters are

$$\begin{aligned}
a &= \sqrt{4(H_{21}H_{12} - H_{11}H_{22})\tau_2 + (\tau_1H_{22} + \tau_2H_{11})^2} \\
b &= 2(H_{21}H_{12} - H_{11}H_{22})\tau_1\tau_2 + (\tau_1H_{22} + \tau_2H_{11})^2 - a(\tau_1H_{22} + \tau_2H_{11}) \\
c &= a[2(\tau_1\tau_2)^2 - b\tau_0^2] \\
d &= 2(H_{21}H_{12} - H_{11}H_{22})\tau_1\tau_2 + (\tau_1H_{22} + \tau_2H_{11})^2 + a(\tau_1H_{22} + \tau_2H_{11}) \\
e &= a[2(\tau_1\tau_2)^2 - d\tau_0^2].
\end{aligned}$$

Obviously, a smaller value of A_ϕ (A_μ) has benefit of repressing the noise propagation in biological networks. Especially $A < 1$ means that the signal fluctuation should decline in propagation on the networks. In contrast, for $A_\phi > 1$ ($A_\mu > 1$), the fluctuations in output is larger than that in the input signal, or the noise is amplified in the network.

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