

Stable Learning

Wen Yu

<https://www.ctrl.cinvestav.mx/~yuw/>
yuw@ctrl.cinvestav.mx

Stable learning

Nonlinear system

$$y(k) = f[X(k)]$$

The neural networks is

$$\hat{y}(k) = W_k \phi[X(k)]$$

If the identified nonlinear system can be represented as (matching condition)

$$y(k) = W^* \phi[X(k)]$$

The training law is

$$W_{k+1} = W_k - \eta \phi e(k)$$

where

$$e(k) = \hat{y}(k) - y(k)$$

$$\begin{aligned}\hat{y}(k) &= W_k \phi \\ y(k) &= W^* \phi\end{aligned}$$

Modeling error is

$$\begin{aligned}e(k) &= \hat{y}(k) - y(k) \\ &= [W_k - W^*] \phi \\ &= \tilde{W}_k \phi\end{aligned}$$

where

$$\tilde{W}_k = W_k - W^*$$

We select Lyapunov function as

$$L_k = \|\tilde{W}_k\|^2 = \text{tr} \left\{ \tilde{W}_k^T \tilde{W}_k \right\}$$

Because

$$\tilde{W}_{k+1} = \tilde{W}_k - \eta_k \phi e(k)$$

From the updating law

$$\begin{aligned} \Delta L_k &= L_{k+1} - L_k = \|\tilde{W}_k - \eta_k \phi e(k)\|^2 - \|\tilde{W}_k\|^2 \\ &= \|\tilde{W}_k\|^2 - 2\eta_k e(k) \phi \tilde{W}_k + \|\eta_k \phi e(k)\|^2 - \|\tilde{W}_k\|^2 \\ &= \eta_k^2 e^2(k) \|\phi\|^2 - 2\eta_k e(k) \phi \tilde{W}_k \\ &= \eta_k^2 e^2(k) \|\phi\|^2 - 2\eta_k e^2(k) \\ &= \left[\eta_k \|\phi\|^2 - 2 \right] \eta_k e^2(k) \end{aligned}$$

We select

$$\eta_k = \frac{2\eta_0}{1 + \|\phi\|^2}, \quad 0 \leq \eta_0 \leq 1$$

then

$$\left[\eta_k \|\phi\|^2 - 2 \right] = 2 \left[\frac{\|\phi\|^2}{1 + \|\phi\|^2} \eta_0 - 1 \right] \leq 2 [\eta_0 - 1] \leq 0$$

so

$$\Delta L_k \leq 0$$

Nonlinear system

$$y(k) = f[X(k)]$$

The neural networks is

$$\hat{y}(k) = W_k \phi[X(k)]$$

If the identified nonlinear system can be represented as

$$y(k) = W^* \phi + \tilde{\zeta}(k), \quad |\tilde{\zeta}|^2 \leq \bar{\zeta}$$

The error dynamic is

$$\begin{aligned}e(k) &= \hat{y}(k) - y(k) \\ &= W_k \phi - W^* \phi - \zeta(k) \\ &= \tilde{W}_k \phi - \zeta(k)\end{aligned}$$

Lyapunov

$$\begin{aligned}\Delta L_k &= \eta_k^2 e^2(k) \|\phi\|^2 - 2\eta_k e(k) \phi \tilde{W}_k \\ &= \eta_k^2 e^2(k) \|\phi\|^2 - 2\eta_k e(k) [e(k) + \zeta(k)] \\ &= \left[\eta_k \|\phi\|^2 - 2 \right] \eta_k e^2(k) - 2\eta_k e(k) \zeta(k)\end{aligned}$$

Here

$$-2\eta_k e(k) \zeta(k) \leq \eta_k e^2(k) + \eta_k \zeta^2(k), \quad \eta_k > 0$$

So

$$\Delta L_k = \left[\eta_k \|\phi[X(k)]\|^2 - 1 \right] \eta_k e^2(k) + \eta_k \tilde{\xi}^2(k)$$

We select

$$\eta_k = \frac{\eta_0}{1 + \|\phi[X(k)]\|^2}, \quad 0 \leq \eta_0 \leq 1$$

then

$$\begin{aligned} & \left[\eta_k \|\phi\|^2 - 1 \right] \eta_k \\ &= \left[\frac{\|\phi\|^2}{1 + \|\phi\|^2} \eta_0 - 1 \right] \eta_k \\ &\leq (\eta_0 - 1) \eta_k = -\pi_k \leq 0 \end{aligned}$$

where

$$\pi_k = (1 - \eta_0) \eta_k$$

So

$$\Delta L_k \leq -\pi_k e^2(k) + \bar{\zeta} \leq -[1 - \eta_0] \bar{\eta} e^2(k) + \bar{\zeta}$$

where

$$\begin{aligned} \pi_k &= \left[1 - \frac{\|\phi\|^2}{1 + \|\phi\|^2} \eta_0 \right] \eta_k \\ &\geq [1 - \eta_0] \eta_k \\ &\geq [1 - \eta_0] \bar{\eta} \end{aligned}$$

here

$$\eta_k = \frac{\eta_0}{1 + \|\phi[X(k)]\|^2} \geq \frac{\eta_0}{1 + \bar{\phi}} = \bar{\eta}, \quad \bar{\phi} = \max \left[\|\phi[X(k)]\|^2 \right]$$

$$W_{k+1} = W_k - s_k \eta_k \phi e(k)$$

where

$$\eta_k = \frac{\eta_0}{1 + \|\phi\|^2}, \quad 0 \leq \eta_0 \leq 1$$

$$s_k = \begin{cases} 1 & \text{if } e^2(k) > \frac{\bar{\xi}}{[1-\eta_0]\bar{\eta}} \\ 0 & \text{if } e^2(k) \leq \frac{\bar{\xi}}{[1-\eta_0]\bar{\eta}} \end{cases}$$

Because

$$\Delta L_k \leq -[1 - \eta_0] \bar{\eta} e^2(k) + \bar{\xi}$$

- If $e^2(k) > \frac{\bar{\xi}}{[1-\eta_0]\bar{\eta}}$, then $\Delta V_k \leq 0$
- If $e^2(k) \leq \frac{\bar{\xi}}{[1-\eta_0]\bar{\eta}}$, $W_{k+1} = W_k$, then $\Delta V_k = 0$

Nonlinear active function

Nonlinear system

$$y(k) = f[X(k)]$$

The neural networks is

$$\hat{y}(k) = \phi[W_k X(k)]$$

We use Talyor serie

$$\begin{aligned}\phi[W_k X(k)] &= \phi(W^0 X) + \phi'(W_k - W^0) X(k) + \mathcal{O}(\tilde{W}) \\ &= \phi(W^0 X) + \phi'(W_k - W^0) X(k) + \delta(k)\end{aligned}$$

The identified nonlinear system can be represented as

$$y(k) = \phi[W^0 X(k)] - \tilde{\xi}(k), \quad |\tilde{\xi}|^2 \leq \bar{\xi}$$

Nonlinear active function

Error dynamic is

$$\begin{aligned}e(k) &= \hat{y}(k) - y(k) = \phi(W_k X) - \phi(W^0 X) + \xi(k) \\ &= \phi'(W_k - W^0) X(k) + \delta(k) + \xi(k) \\ &= \phi' \tilde{W}_k X(k) + \delta(k) + \xi(k)\end{aligned}$$

Training law should be

$$W_{k+1} = W_k - \eta_k \phi' X(k) e(k)$$

Nonlinear active function

Because

$$\begin{aligned}\tilde{W}_{k+1} &= \tilde{W}_k - \eta_k \phi' X(k) e(k) \\ e(k) &= \phi' \tilde{W}_k X(k) + \delta(k) + \xi(k)\end{aligned}$$

Lyapunov

$$\begin{aligned}\Delta L_k &= \eta_k^2 e^2(k) \|\phi' X(k)\|^2 - 2\eta_k e(k) \phi' \tilde{W}_k X(k) \\ &= \eta_k^2 e^2(k) \|\phi' X(k)\|^2 \\ &\quad - 2\eta_k e(k) [e(k) - \delta(k) - \xi(k)] \\ &= \left[\eta_k \|\phi' X(k)\|^2 - 2 \right] \eta_k e^2(k) \\ &\quad + 2\eta_k e(k) [\delta(k) + \xi(k)]\end{aligned}$$

Here

$$2\eta_k e(k) [\delta(k) + \xi(k)] \leq \eta_k e^2(k) + \eta_k (\bar{\xi} + \bar{\delta}), \quad \eta_k > 0$$

Nonlinear active function

So

$$\Delta L_k \leq -[1 - \eta_0] \bar{\eta} e^2(k) + (\bar{\xi} + \bar{\delta})$$

Then the training law is

$$W_{k+1} = W_k - s_k \eta_k \phi' X(k) e(k)$$

where

$$\eta_k = \frac{\eta_0}{1 + \|\phi\|^2}, \quad 0 \leq \eta_0 \leq 1$$

$$s_k = \begin{cases} 1 & \text{if } e^2(k) > \frac{\bar{\xi} + \bar{\delta}}{[1 - \eta_0] \bar{\eta}} \\ 0 & \text{if } e^2(k) \leq \frac{\bar{\xi} + \bar{\delta}}{[1 - \eta_0] \bar{\eta}} \end{cases}$$

$$\bar{\eta} = \frac{\eta_0}{1 + \bar{\phi}}, \quad \bar{\phi} = \max \left[\|\phi[X(k)]\|^2 \right]$$

Nonlinear system

$$y(k) = f[X(k)]$$

MLP neural networks is

$$\hat{y}(k) = W_k \phi[V_k X(k)]$$

The identified nonlinear system can be represented as

$$y(k) = W^0 \phi[V^0 X(k)] - \xi(k), \quad |\xi|^2 \leq \bar{\xi}$$

We use Talyor seris

$$\begin{aligned} \phi[V_k X(k)] &= \phi(V^0 X) + \phi'(V_k - V^0) X(k) + \delta(k) \\ \phi[V_k X(k)] - \phi(V^0 X) &= \phi' \tilde{V}_k X(k) + \delta(k) \end{aligned}$$

The error dynamic is

$$\begin{aligned}
 e(k) &= W_k \phi [V_k X(k)] - W^0 \phi [V^0 X(k)] + \xi(k) \\
 &= W_k \phi [V_k X(k)] - W^0 \phi [V^0 X(k)] \\
 &\quad + W^0 \phi [V_k X(k)] - W^0 \phi [V_k X(k)] + \xi(k) \\
 &= \tilde{W}_k \phi [V_k X(k)] + W^0 [\phi [V_k X(k)] - \phi [V^0 X(k)]] + \xi(k) \\
 &= \tilde{W}_k \phi [V_k X(k)] + W^0 \phi' \tilde{V}_k X(k) + \delta(k) + \xi(k)
 \end{aligned}$$

Training law should be

$$\begin{aligned}
 W_{k+1} &= W_k - \eta_k \phi [V_k X(k)] e(k) \\
 V_{k+1} &= V_k - \eta_k W^0 \phi' X(k) e(k)
 \end{aligned}$$

Lyapunov

$$L_k = \|\tilde{W}_k\|^2 + \|\tilde{V}_k\|^2$$

$$\begin{aligned} \Delta L_k &= \|\tilde{W}_{k+1}\|^2 + \|\tilde{V}_{k+1}\|^2 - \left(\|\tilde{W}_k\|^2 + \|\tilde{V}_k\|^2 \right) \\ &= \|\tilde{W}_k - \eta_k \phi[V_k X(k)] e(k)\|^2 + \|\tilde{V}_k - \eta_k W^0 \phi' X(k) e(k)\|^2 \\ &\quad - \left(\|\tilde{W}_k\|^2 + \|\tilde{V}_k\|^2 \right) \\ &= \|\eta_k \phi[V_k X(k)] e(k)\|^2 + \|\eta_k W^0 \phi' X(k) e(k)\|^2 \\ &\quad - 2\eta_k \phi[V_k X(k)] e(k) \tilde{W}_k - 2\eta_k W^0 \phi' X(k) e(k) \tilde{V}_k \\ &= \|\eta_k \phi[V_k X(k)] e(k)\|^2 + \|\eta_k W^0 \phi' X(k) e(k)\|^2 \\ &\quad - 2\eta_k \left\{ \tilde{W}_k \phi[V_k X(k)] + W^0 \phi' \tilde{V}_k X(k) \right\} e(k) \end{aligned}$$

Because

$$\tilde{W}_k \phi [V_k X(k)] + W^0 \phi' \tilde{V}_k X(k) = e(k) - \delta(k) - \xi(k)$$

$$\begin{aligned} \Delta L_k &= \|\eta_k \phi [V_k X(k)] e(k)\|^2 + \|\eta_k W^0 \phi' X(k) e(k)\|^2 \\ &\quad - 2\eta_k \{e(k) - \delta(k) - \xi(k)\} e(k) \\ &= -\eta_k \left[2 - \eta_k \left(\|\phi V_k X(k)\|^2 + \|W^0 \phi' X(k)\|^2 \right) \right] e^2(k) \\ &\quad + 2\eta_k e(k) [\delta(k) + \xi(k)] \end{aligned}$$

Let

$$\eta_k = \frac{\eta_0}{1 + \|\phi V_k X(k)\|^2 + \|W^0 \phi' X(k)\|^2}, \quad 1 \geq \eta_0 > 0$$

Because

$$2\eta_k e(k) [\delta(k) + \xi(k)] \leq \eta_k e^2(k) + \eta_k (\bar{\xi} + \bar{\delta}), \quad 1 \geq \eta_k > 0$$

So

$$\begin{aligned} \Delta L_k &\leq \eta_k \left[\eta_k \left(\|\phi V_k X(k)\|^2 + \|W^0 \phi' X(k)\|^2 \right) - 1 \right] e^2(k) \\ &\quad + \eta_k (\bar{\xi} + \bar{\delta}) \\ &\leq \eta_k \left[\frac{(\|\phi V_k X(k)\|^2 + \|W^0 \phi' X(k)\|^2)}{1 + \|\phi V_k X(k)\|^2 + \|W^0 \phi' X(k)\|^2} \eta_0 - 1 \right] e^2(k) + \bar{\xi} + \bar{\delta} \\ &\leq -\pi_k e^2(k) + \bar{\xi} + \bar{\delta} \\ &\leq -[1 - \eta_0] \bar{\eta} e^2(k) + \bar{\xi} + \bar{\delta} \end{aligned}$$

where

$$\bar{\eta} = \frac{\eta_0}{1 + \bar{\phi}}, \quad \bar{\phi} = \max \left[\|\phi V_k X(k)\|^2 + \|W^0 \phi' X(k)\|^2 \right]$$

Then the training law is

$$\begin{aligned}W_{k+1} &= W_k - s_k \eta_k \phi [V_k X(k)] e(k) \\V_{k+1} &= V_k - s_k \eta_k W^0 \phi' X(k) e(k)\end{aligned}$$

where

$$\eta_k = \frac{\eta_0}{1 + \|\phi V_k X(k)\|^2 + \|W^0 \phi' X(k)\|^2}, \quad 0 \leq \eta_0 \leq 1$$

$$s_k = \begin{cases} 1 & \text{if } e^2(k) > \frac{\bar{\xi} + \bar{\delta}}{[1 - \eta_0] \bar{\eta}} \\ 0 & \text{if } e^2(k) \leq \frac{\bar{\xi} + \bar{\delta}}{[1 - \eta_0] \bar{\eta}} \end{cases}$$

The average of the identification error

Because

$$\Delta L_k \leq - [1 - \eta_0] \bar{\eta} e^2(k) + \bar{\xi} + \bar{\delta}$$

Summarizing from 1 up to T , and by using $L_T > 0$ and L_1 is a constant, we obtain

$$\begin{aligned} L_T - L_1 &\leq - [1 - \eta_0] \bar{\eta} \sum_{k=1}^T e^2(k) + T (\bar{\xi} + \bar{\delta}) \\ [1 - \eta_0] \bar{\eta} \sum_{k=1}^T e^2(k) &\leq L_1 - L_T + T (\bar{\xi} + \bar{\delta}) \\ &\leq L_1 + T (\bar{\xi} + \bar{\delta}) \end{aligned}$$

so

$$\frac{1}{T} \sum_{k=1}^T e^2(k) \leq \frac{\bar{\xi} + \bar{\delta}}{[1 - \eta_0] \bar{\eta}} + \frac{1}{T} \frac{1}{[1 - \eta_0] \bar{\eta}} L_1$$

$$\limsup_{T \rightarrow \infty} \frac{1}{T} \sum_{k=1}^T e^2(k) \leq \frac{\bar{\xi} + \bar{\delta}}{[1 - \eta_0] \bar{\eta}}$$

W^0 does not effect the stability property of the neuro identification, but it influences the identification accuracy.

- 1 Start from any initial value for $W^0 = W_0$.
- 2 Do identification with this W^0 until T_0 .
- 3 If the $\|e(T_0)\| < \|e(0)\|$, let W_T as a new W^0 , i.e., $W^0 = W_{T_0}$, go to 2 to repeat the identification process.
- 4 If the $\|e(T_0)\| \geq \|e(0)\|$, stop this off-line identification, now W_{T_0} is the final value for W^0 .

With this prior knowledge W^0 , we may start the on-line identification .