결합 외란 조건하에서의 강인 전륜 조향 경로 추종을 위한 종단 간 온라인 LSTM 제어

End-to-End Online LSTM Control for Robust 4WS Path Tracking under Combined Disturbances

○에레가 나올 사무엘[1], 최경환[2*]
[1)]한국과학기술원 조천식모빌리티대학원 (TEL: +8210-7940-6684; E-mail: samuelnaol7@kaist.ac.kr)
[2)]한국과학기술원 조천식모빌리티대학원 (TEL: +82-42-350-1764; E-mail: kh.choi@kaist.ac.kr)

Abstract We propose a continuous-time LSTM neural network as an end-to-end controller for four-wheel steering (4WS) path tracking. Without offline data, reference models, or expert demonstrations, the network learns entirely online from real-time tracking error, mapping lateral offset and heading error to front and rear steering commands. We evaluate the controller on a slalom track under simultaneous actuator bias, Ornstein–Uhlenbeck (OU) colored noise, and a sharp lateral wind gust. The LSTM weights converge within a few episodes and, crucially, tracking performance degrades by less than 2% under combined disturbances. A tuned PID baseline, by contrast, suffers up to 46% lateral and 21% heading RMSE increases under identical conditions. This difference suggests that online LSTM adaptation provides greater robustness to combined disturbances compared to fixed-gain control.

Keywords end-to-end control; LSTM; four-wheel steering; online adaptation; robustness

1. 서론

End-to-end controllers that map tracking errors directly to actuator commands require no explicit vehicle model and can adapt online to unmodeled uncertainty. LSTM networks [1] are well suited here, as their gated cell state captures transient dynamics across the control horizon. Four-wheel steering (4WS) amplifies the need for such robustness, since independent front and rear steering is sensitive to actuator imperfections and external disturbances [2].

We investigate a continuous-time LSTM [3], updated online via a Lyapunov-guided gradient rule [4], as an end-to-end 4WS controller, and compare it against a tuned PID under nominal conditions and combined disturbances (actuator bias, OU noise, and a lateral wind gust).

2. 차량 모델 및 제어기 설계

2.1. 차량 모델

We use a 4WS vehicle bicycle model at constant speed v_x:

$$\begin{cases} \frac{d}{dt}r = \frac{l_f F_{y,f} - l_r F_{y,r}}{I_z}, \\ \frac{d}{dt}v_y = \frac{F_{y,f}+F_{y,r}}{m} - v_x r, \end{cases} \tag{1}$$

where r is yaw rate, v_y lateral velocity, m mass, I_z yaw inertia, and l_f, l_r front and rear axle distances [2]. Lateral tire forces follow the nonlinear model

$$\alpha_i = \delta_i - \frac{v_y \pm l_i r}{v_x}, \quad F_{y,i} = F_{\max}\tanh\!\Big(\frac{C_i}{F_{\max}}\alpha_i\Big), \tag{2}$$

for $i \in \{f,r\}$, slip and steering angles α_i,δ_i, cornering stiffness C_i, and saturation force $F_{\max}$. The state is $x = (X,Y,\psi,v_y,r)^\top$ and the end-to-end control output is $\boldsymbol{\Phi} = (\delta_f,\delta_r)^\top$.

2.2. 종단 간 온라인 LSTM 제어기

We adopt the continuous-time LSTM of [3] with hidden state $h \in \mathbb{R}^{l_2}$ and cell state $c \in \mathbb{R}^{l_2}$, LSTM input vector $z = (e_y,e_\psi,h_1,\dots,h_{l_2},1)^\top$. The gate dynamics and cell/hidden state evolution follow [3, Eq. 5] with user-defined gains $b_c,b_h > 0$. The steering command is

$$\boldsymbol{\Phi} = \mathbf{W}_{\mathbf{h}}^{T}\big(\boldsymbol{h} + \tanh(\boldsymbol{W}_{ff}^{T}\boldsymbol{e})\big), \qquad \boldsymbol{e} = (\boldsymbol{e}_y, \boldsymbol{e}_\psi)^{T}. \tag{3}$$

2.3. 가중치 적응 법칙 설계

Weights are updated at each control step to minimize

$$J = \frac{1}{2}e^T Q e + \frac{1}{2}\boldsymbol{\Phi}^{\mathbf{T}}\boldsymbol{R}\boldsymbol{\Phi}, \tag{4}$$

with Q,R ≥ 0 user-defined weight matrices. Using the sensitivity approximation $\partial e/\partial\boldsymbol{\Phi} \approx \mathbf{I}$ and learning rate η:

$$vec(\boldsymbol{W}_j^{k+1}) \leftarrow vec(\boldsymbol{W}_j^{k}) - \eta\left(\frac{\partial\boldsymbol{\Phi}}{\partial vec(\boldsymbol{W}_j^{T})}\right)^{\boldsymbol{T}}(\boldsymbol{Qe} + \boldsymbol{R\Phi}), \tag{5}$$

for $j \in \{f,i,o,c,h,\mathrm{ff}\}$, corresponding to the forget, input, output, cell, hidden, and feedforward weight matrices, respectively, and vec(·) denotes matrix vectorization. The weights evolve solely from the tracking error during operation [4].

표 **1.** 슬라럼 경로 RMSE (에피소드 10).

Ctrl	Scen.	Unperturbed Initial		Perturbed Initial	
		e_y (m)	e_ψ (deg)	e_y (m)	e_ψ (deg)
PID	N	0.039	2.86	0.121	3.68
PID	N+D	0.057	3.47	0.138	4.27
LSTM	N	0.053	2.51	0.126	3.23
LSTM	N+D	0.054	2.55	0.132	3.36

3. 실험 및 분석

3.1. 실험 설정

Simulations are conducted at constant speed vx = 5m/s with dynamics integrated at 1 kHz and control updated at 100 Hz. Tracking errors e_y and e_ψ are computed by projecting the vehicle onto a sinusoidal slalom centerline with a 1.25 m look-ahead. Two initial conditions are tested: zero error and a lateral offset ($Y_0 = -1$ m). LSTM weights are retained across episodes. PID gains are tuned for the nominal plant. We denote nominal (undisturbed) runs as N and combined-disturbance runs as N+D.

Disturbance model: Steering bias b = $[0.05, 0.02]^\top$ rad (front, rear) and OU noise ($\sigma = [0.01, 0.01]^\top$rad, $\tau = 0.2$ s) are added to control inputs. A lateral wind gust $F_w = 4500$N (yaw moment $M_w = 2250$Nm, $d_w = 0.5$m ahead of CG) is applied during $t \in [8, 9]$s.

3.2. 실험 결과 분석 및 고찰

Lateral and heading root-mean-square error (RMSE) values for both controllers are summarized in 표 1. LSTM results are reported at episode 10. Both tracking errors e_y and e_ψ RMSE drop sharply after episode 1 and plateau by episode 3–4 (그림. 1), confirming rapid convergence of LSTM without offline pre-training.

Under nominal conditions, PID achieves lower lateral RMSE (0.039 m) than LSTM (0.053 m). However, when combined disturbances are applied, PID lateral RMSE rises 46% while LSTM degrades by less than 2%, as online adaptation continuously compensates for bias, noise, and the wind gust. The same trend holds under the offset initial condition, where PID degrades by 14–16% compared to 4–5% for LSTM.

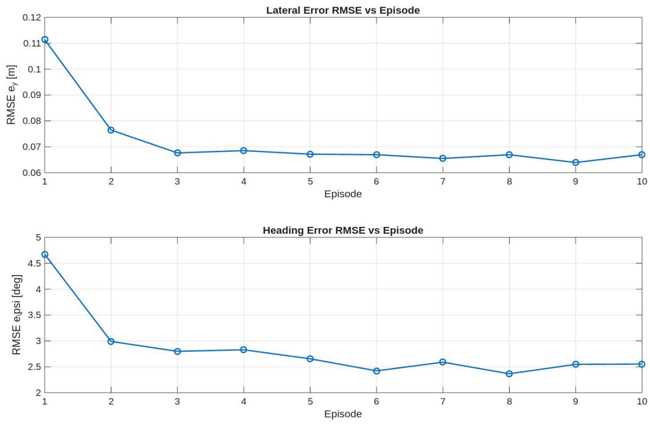

그림 1. 외란 조건하에서의 에피소드별 LSTM RMSE.

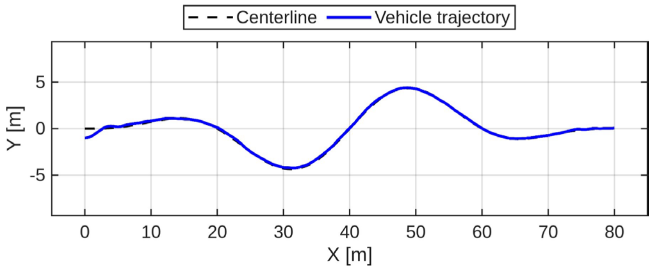

그림 **2.** 결합 외란 조건하에서의 LSTM 슬라럼 궤적 (에피소드 10)

4. 결론

The proposed continuous-time LSTM controller converges online within a few episodes and maintains near-nominal 4WS path-tracking performance under combined disturbances, whereas a tuned PID degrades noticeably. This robustness comes at the cost of slightly higher lateral error under nominal conditions. Future work will explore variable speed, sharper tracks, and formal stability guarantees for the adaptation law.

참고문헌

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