AI-based WEARable Robotics
AWEAR Lab

Assist와 Resist, 그리고 최적화

2025-02-17

지난번 미팅

내용

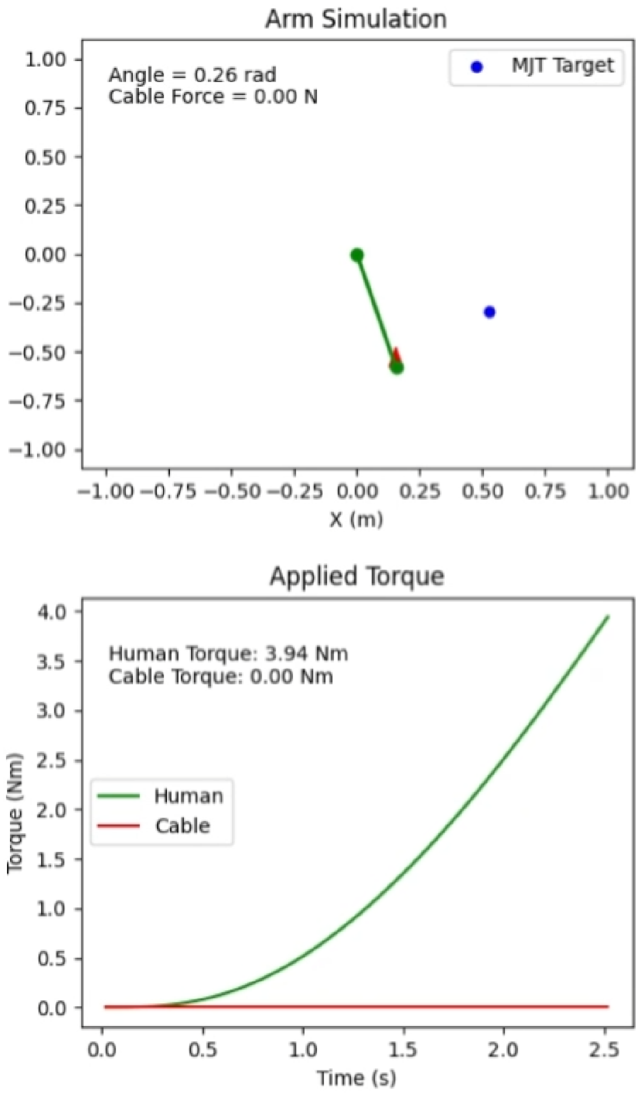
- HW에서 low P제어 구현
- HW에서 Constant한 힘을 베이지안 최적화

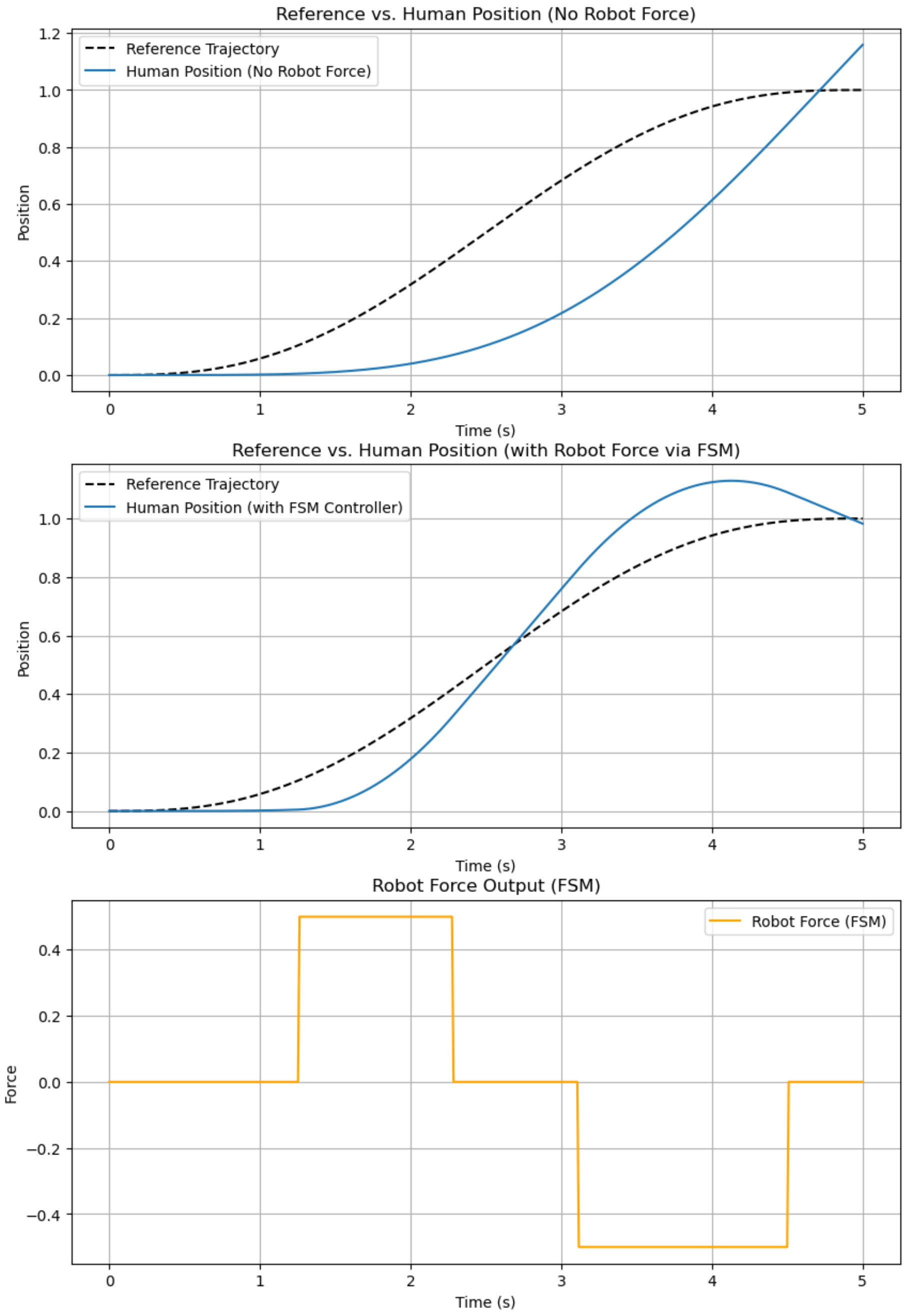
문제점

최적화 범위가 넓어서 탐색 범위가 너무 크다.

목표

- Rule-based로 assist, resist 위치 파악 후 강도만 최적화
- 알고리즘 시뮬레이션 구현, ~~HW 구현~~





Assist, Resist의 구별
간단한 rule-based FSM (Finite State Machine)

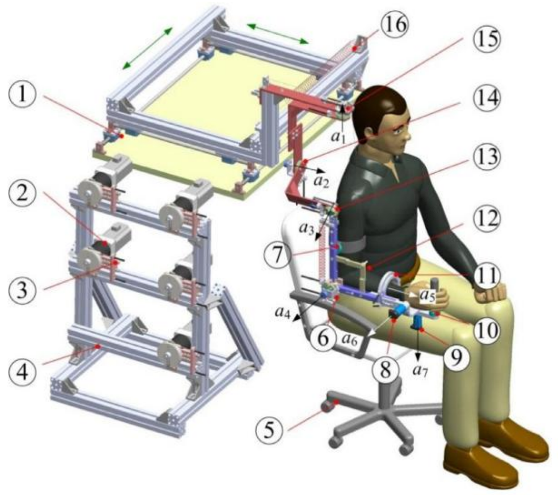
구조

- Ref 궤적과의 오차가 threshold 이상으로 커지면 오차 부호에 따라 assist, resist를 구별한다.
- 강도는 베이지안 최적화한다.

문제점

- 불연속적인 힘을 가하기 때문에 추가적인 기법 필요
- Assist와 resist를 개별적으로 최적화 필요
  - 탐색 범위가 큰 상태에서 변수까지 증가
- 궤적을 잘 따라가기 위한 미세조정이 불가능

논문1 참고



[HTML] Development of an RBFN-based neural-fuzzy adaptive control strategy for an upper limb rehabilitation exoskeleton

Q Wu, X Wang, B Chen, H Wu - Mechatronics, 2018 - Elsevier

The patients of paralysis with motion impairment problems require extensive rehabilitation programs to regain motor functions. The great labor intensity and limited therapeutic effect of traditional human-based manual treatment have recently boosted the development of robot-assisted rehabilitation therapy. In the present work, a neural-fuzzy adaptive controller (NFAC) based on radial basis function network (RBFN) is developed for a rehabilitation exoskeleton to provide human arm movement assistance. A comprehensive overview is ...

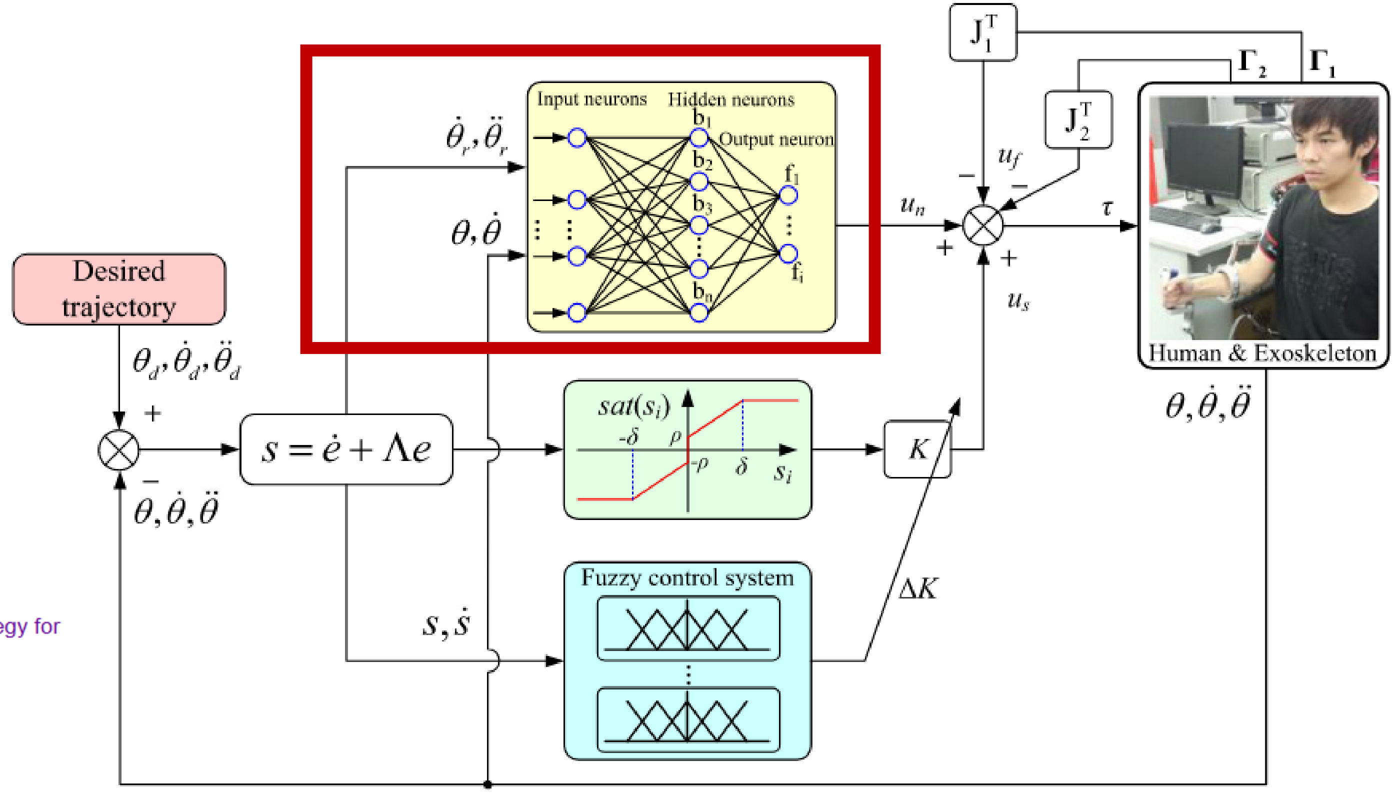


Fig. 6. Overall block diagram of the proposed RBFN-based neural-fuzzy adaptive control strategy.

RNFN + SMC + Fuzzy

시스템 모델을 RBFN으로 학습했다. Fuzzy는 SMC에서의 chattering 문제를 해결

기존의 SMC

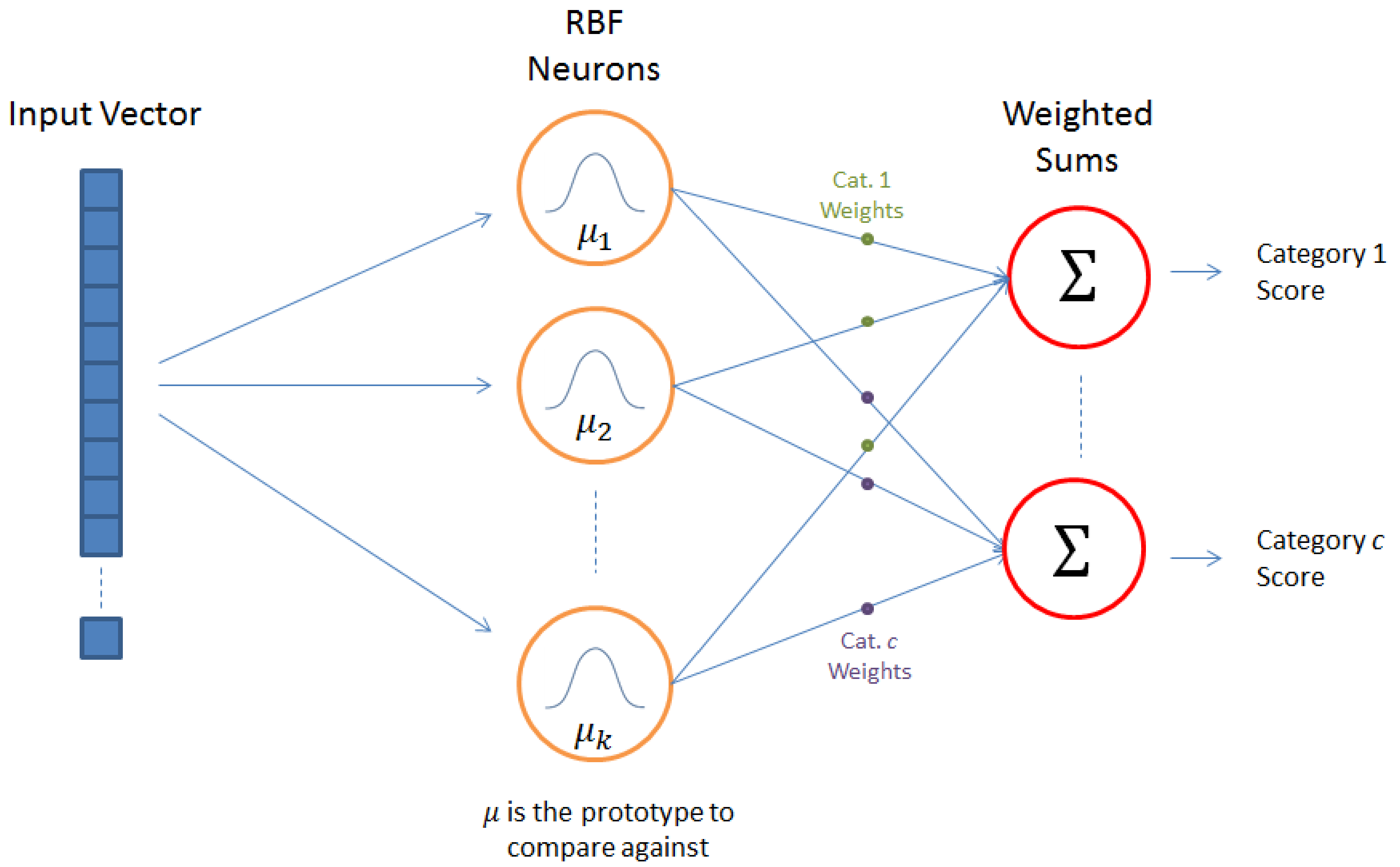
$$\boxed{\tau = M(\theta)\ddot{\theta}_d + C(\theta,\dot{\theta})\dot{\theta} + G(\theta) - K\,\mathrm{sgn}(s)}$$

$$f(x) = M(\theta)\ddot{\theta}_r + V(\theta, \dot{\theta})\dot{\theta}_r + \tau_f(\theta, \dot{\theta})$$

$$\Downarrow$$

$$f(x) = W^{*T}\phi(x) + \varepsilon(x)$$

RBFN



RBF
Neurons
Input Vector
Weighted
Sums
Cat. 1
Weights
μ_1
μ_2
μ_k
Σ
Σ
Category 1
Score
Category c
Score
Cat. c
Weights
μ is the prototype to
compare against

논문2 참고

Pneu-WREX의 Adaptive Control

Optimizing compliant, model-based robotic assistance to promote neurorehabilitation

ET Wolbrecht, V Chan, DJ Reinkensmeyer, JE Bobrow

IEEE Transactions on Neural Systems and Rehabilitation Engineering, 2008 · ieeexplore.ieee.org

Based on evidence from recent experiments in motor learning and neurorehabilitation, we hypothesize that three desirable features for a controller for robot-aided movement training following stroke are high mechanical compliance, the ability to assist patients in completing desired movements, and the ability to provide only the minimum assistance necessary. This paper presents a novel controller that successfully exhibits these characteristics. The controller uses a standard model-based, adaptive control approach in

자세히 보기

☆ 저장 99 인용 565회 인용 관련 학술자료 전체 13개의 버전 Web of Science: 360

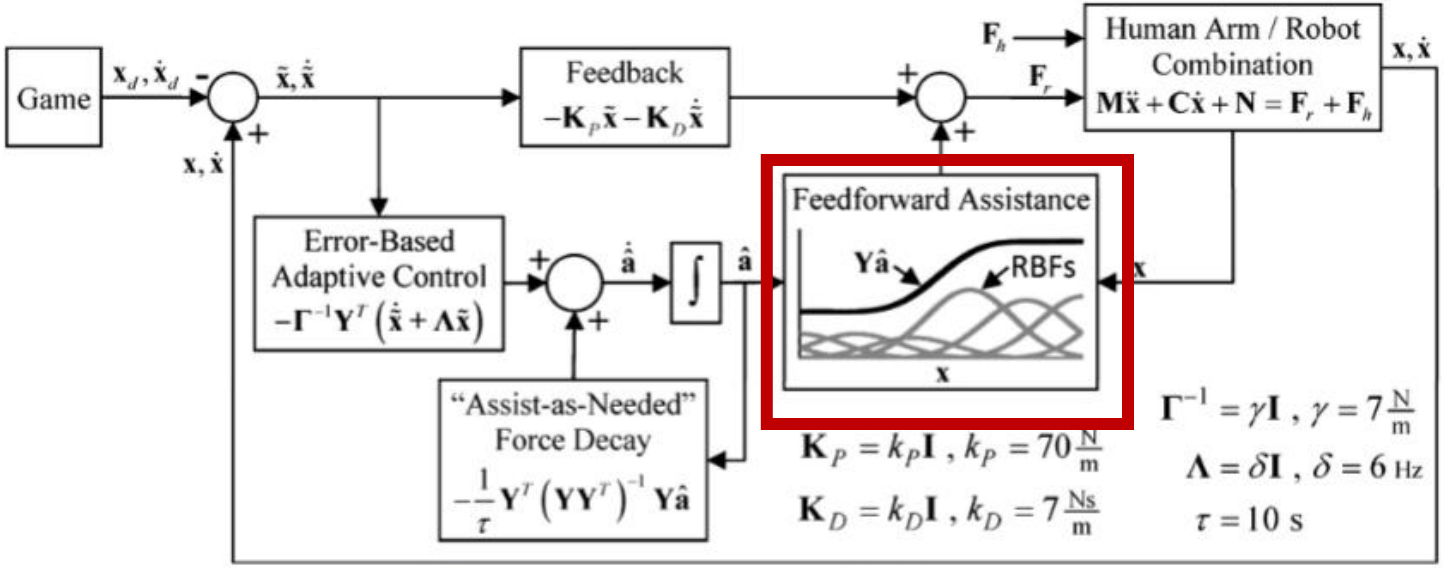


Fig. 2. Controller diagram. The "assist-as-needed" force decay term continuously reduces the feedforward assistance when errors are small. Feedforward assistance is a learned model of the subject's abilities and effort using radial basis functions. Gains of the controller are given in the figure. The effective integral, proportional, and derivative gains, taking into account the adaptive action of the controller, are derived in the Appendix.

RBF들의 조합을 이용해서 assist force를 만들었다.

$$\dot{\hat{a}} = -\boldsymbol{\Gamma}^{-1}\mathbf{Y}^T\mathbf{s}$$

Weight를 위와 같이 업데이트를 한다.

논문2 참고

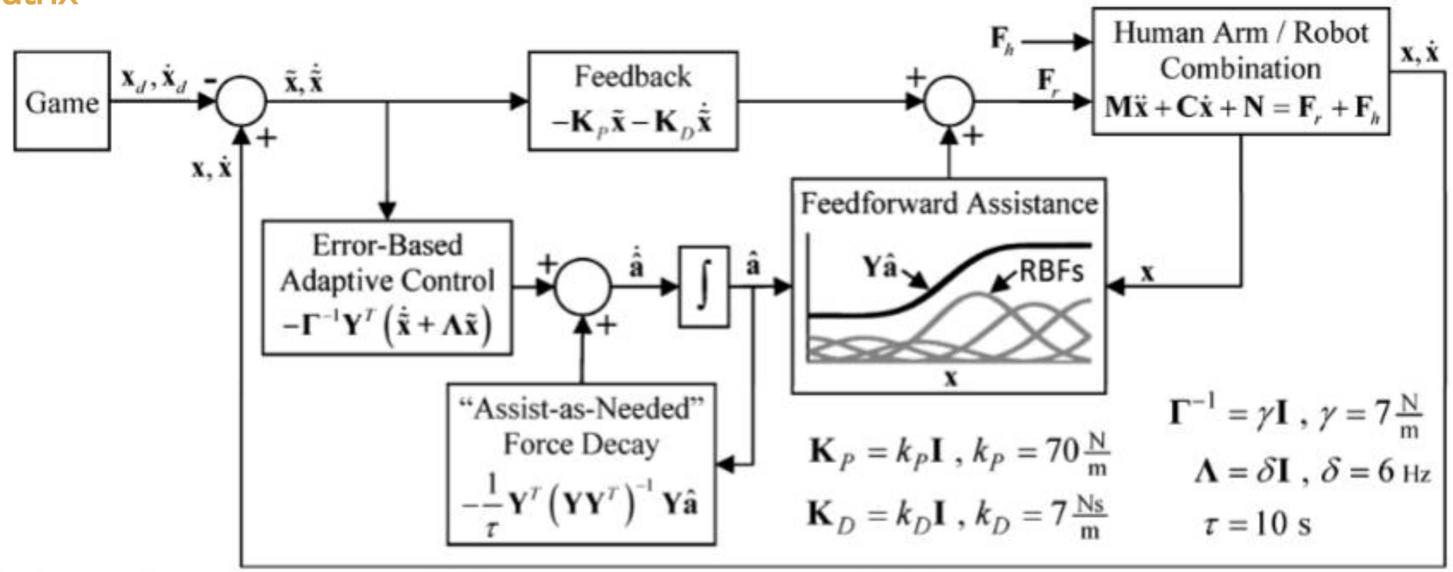
Learning rate RBF Regressor Matrix

Weight $$\dot{\hat{a}} = -\Gamma^{-1}\mathbf{Y}^T\mathbf{s}$$

$$s = \dot{\tilde{x}} + \Lambda\tilde{x}$$ Sliding surface

$$\mathbf{Y}^{3\times 360} = \left[\begin{array}{c:c:c} \mathbf{g}^T & 0 & 0 \\ \hdashline 0 & \mathbf{g}^T & 0 \\ \hdashline 0 & 0 & \mathbf{g}^T \end{array}\right]$$

$$g_n = \exp\left(-\frac{|\mathbf{x}-\boldsymbol{\mu}_n|^2}{2\sigma^2}\right)$$



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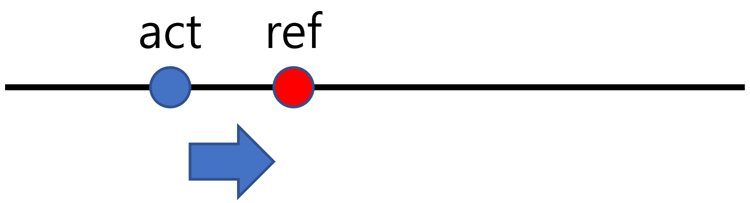
"the parameters representing the amount of force the subject is unable to provide to hold their arm at a particular location in space."

"Ya is the model based feedforward force applied to the subject′s arm by the adaptive controller"

시뮬레이션



시스템 환경

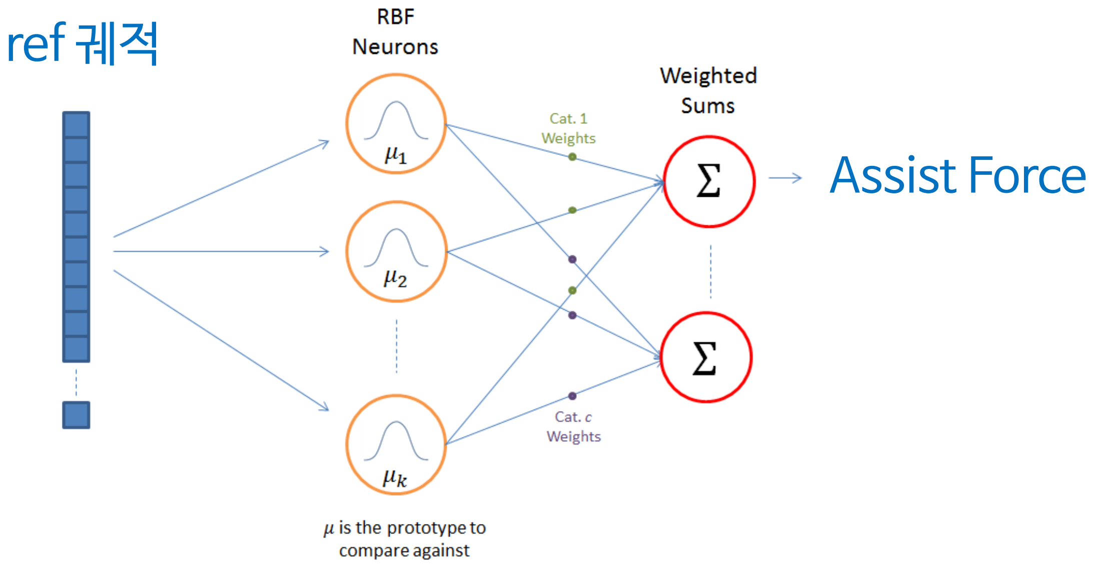
- linear path
- MJT trajectory

사람 + 로봇 시스템을

Mass-Spring-Damper System으로 가정

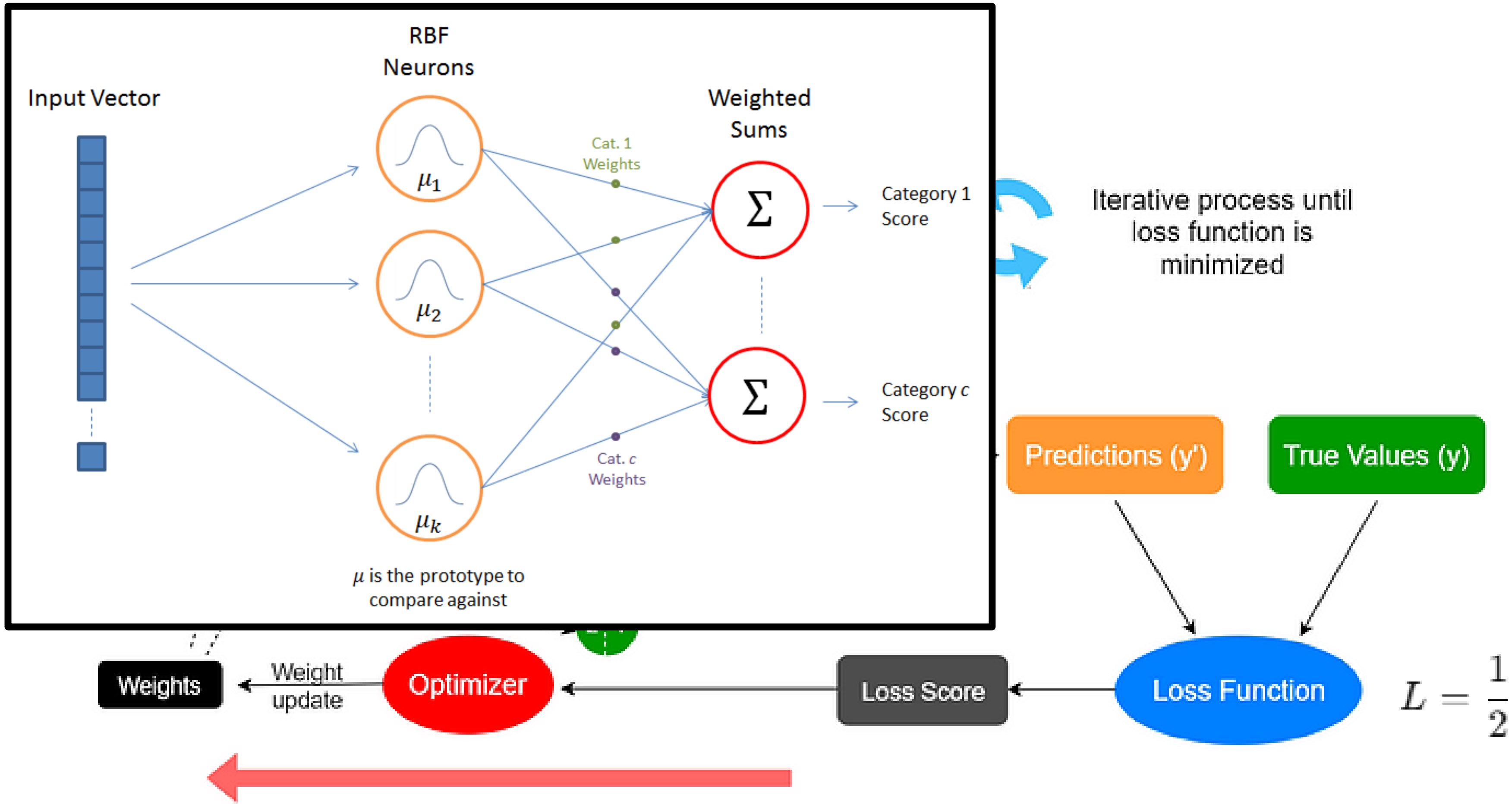
- Mass : 1kg
- Damper : 5N/s
- Spring : 사람마다 변이

RBFN이 위 모델을 학습하도록 한다.



시뮬레이션

$$f_{\text{rbfn}} = \sum_{i=1}^{n} w_i \cdot \phi_i(x_{\text{ref}})$$



$$L = \frac{1}{2}(x_{\text{ref}} - x)^2$$

Backward Propagation

SGD

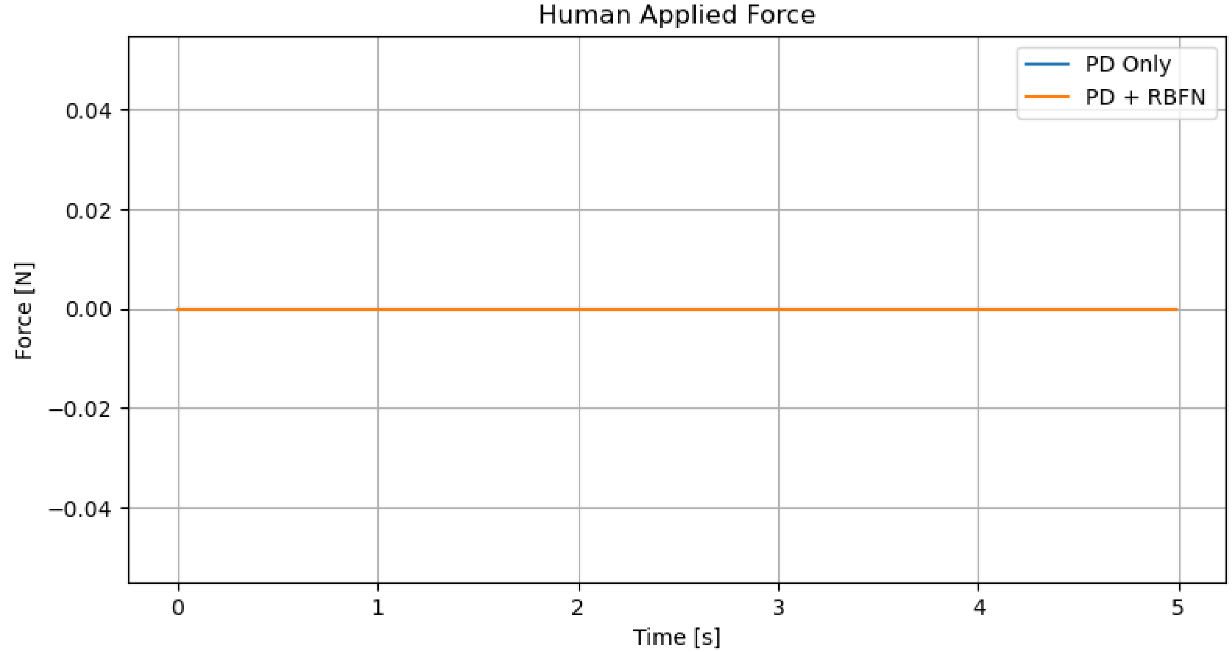
$$\frac{\partial L}{\partial w_i} = \frac{\partial L}{\partial x} \cdot \frac{\partial x}{\partial w_i} = -(x_{\text{ref}} - x) \cdot \phi_i(x_{\text{ref}})$$

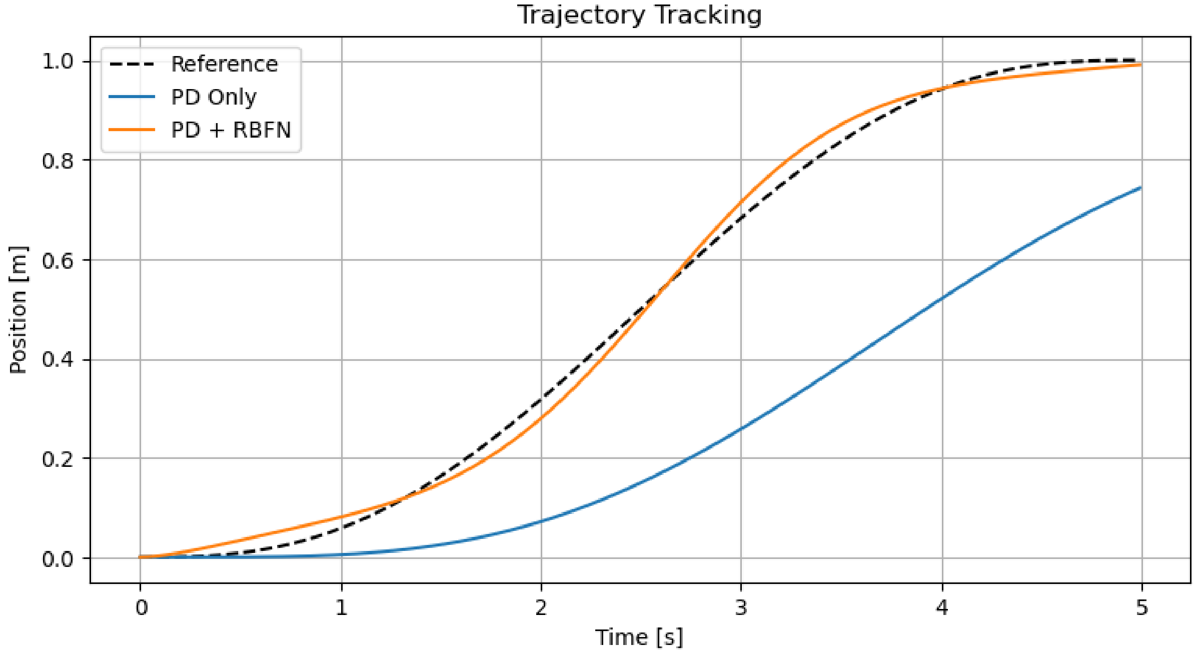
$$w_i \leftarrow w_i + \eta \cdot (x_{\text{ref}} - x) \cdot \phi_i(x_{\text{ref}}) \cdot dt$$

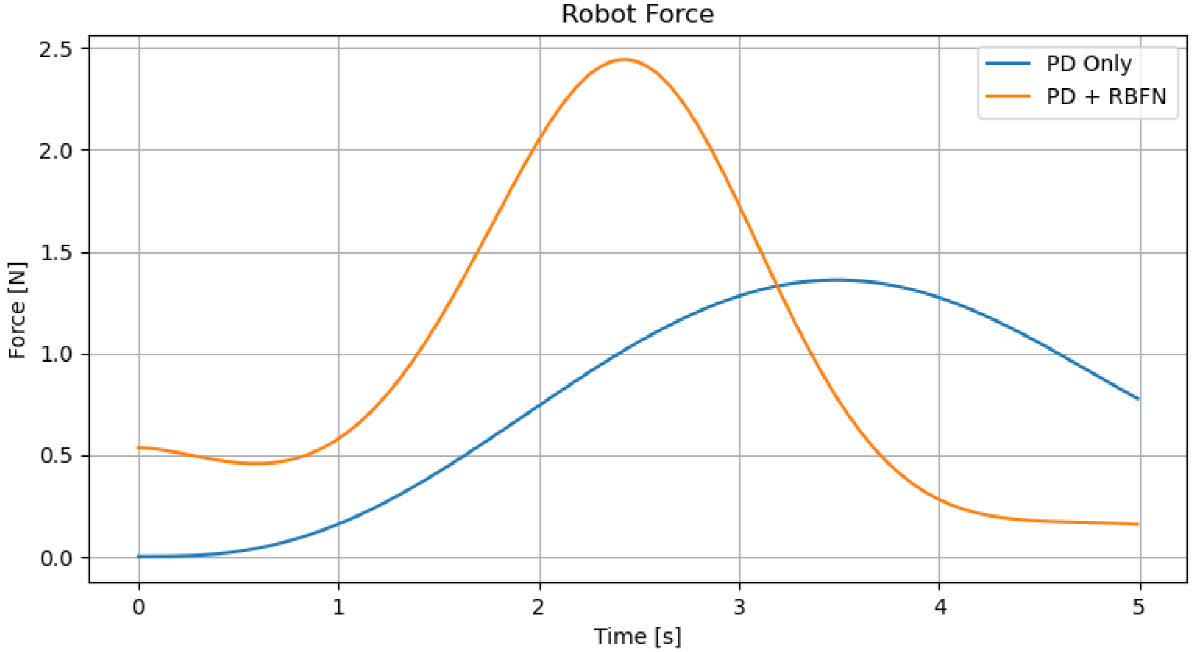
Lyapunov-based

$$V(t) = \frac{1}{2}\mathbf{s}^T\mathbf{M}\mathbf{s} + \frac{1}{2}\tilde{\mathbf{x}}^T(\mathbf{K}_P + \mathbf{\Lambda}\mathbf{K}_D)\tilde{\mathbf{x}} + \frac{1}{2}\tilde{\mathbf{a}}^T\mathbf{\Gamma}\tilde{\mathbf{a}}$$

Human "A" Final Cycle Control Comparison



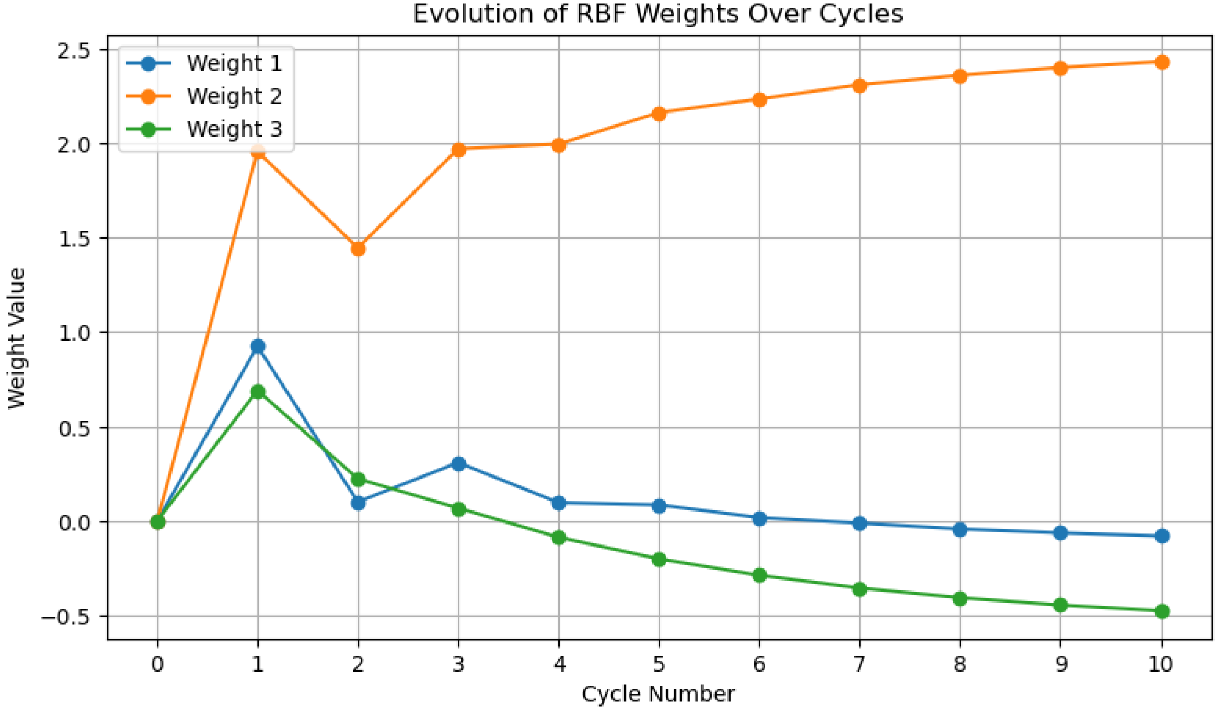


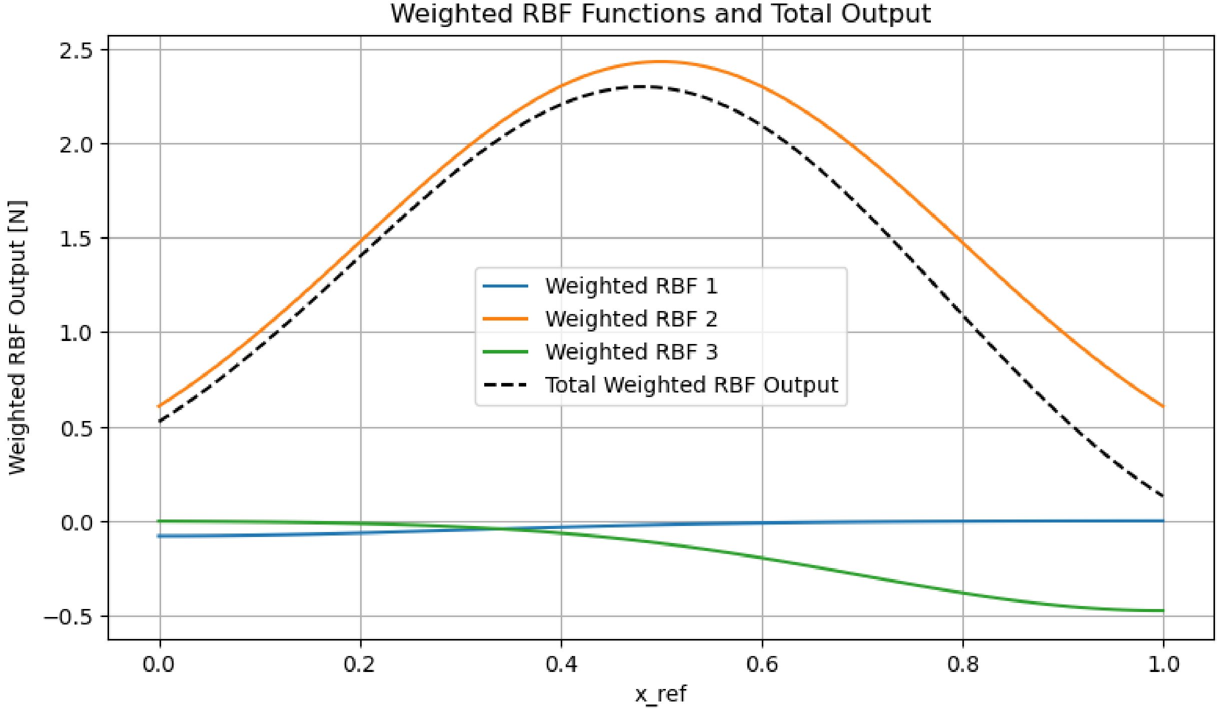


$$u_{total} = u_{pid} + u_{human} + u_{rbfn}$$

힘을 아에 못내는 사람

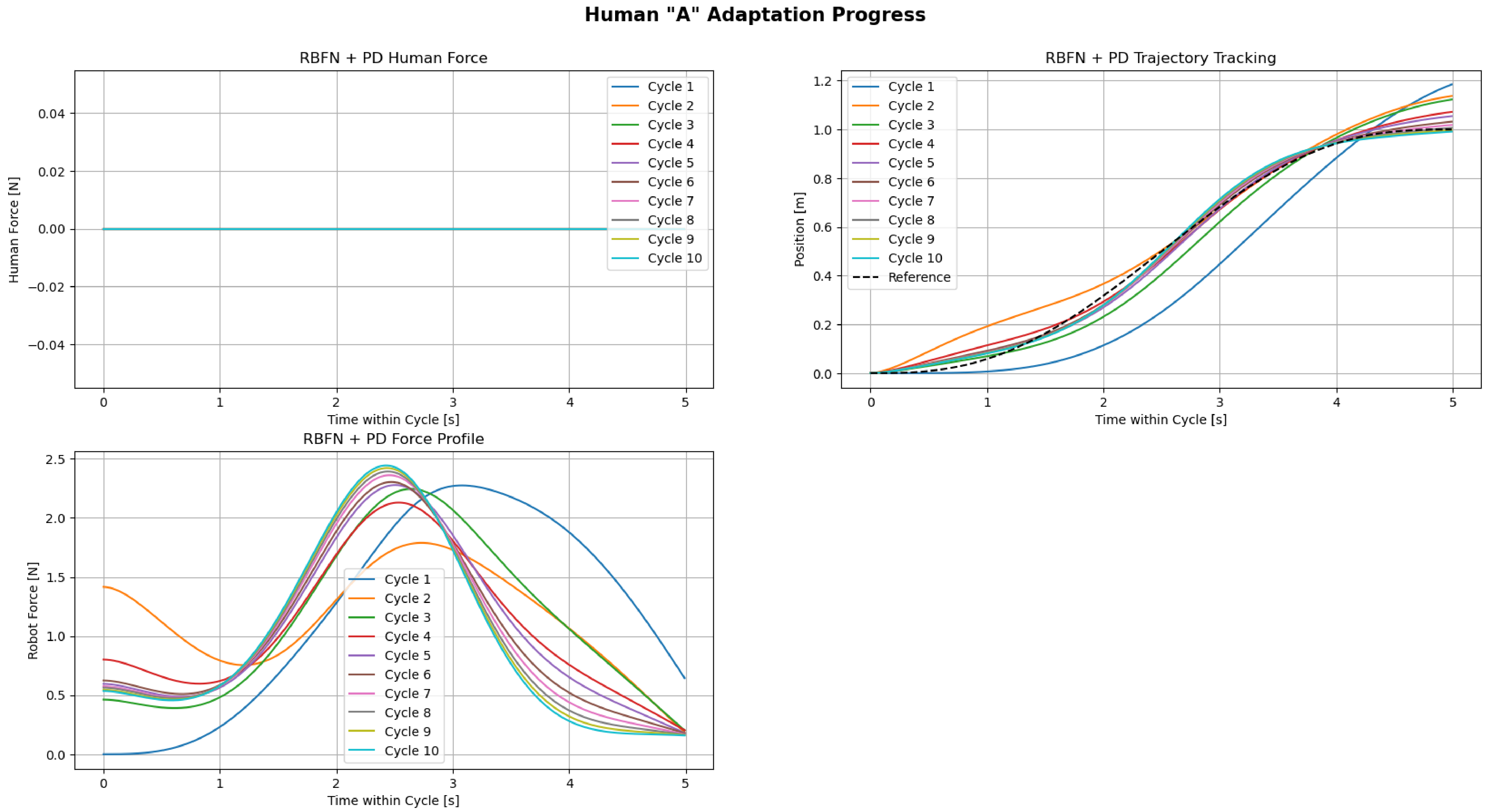
Human "A" RBFN Weight



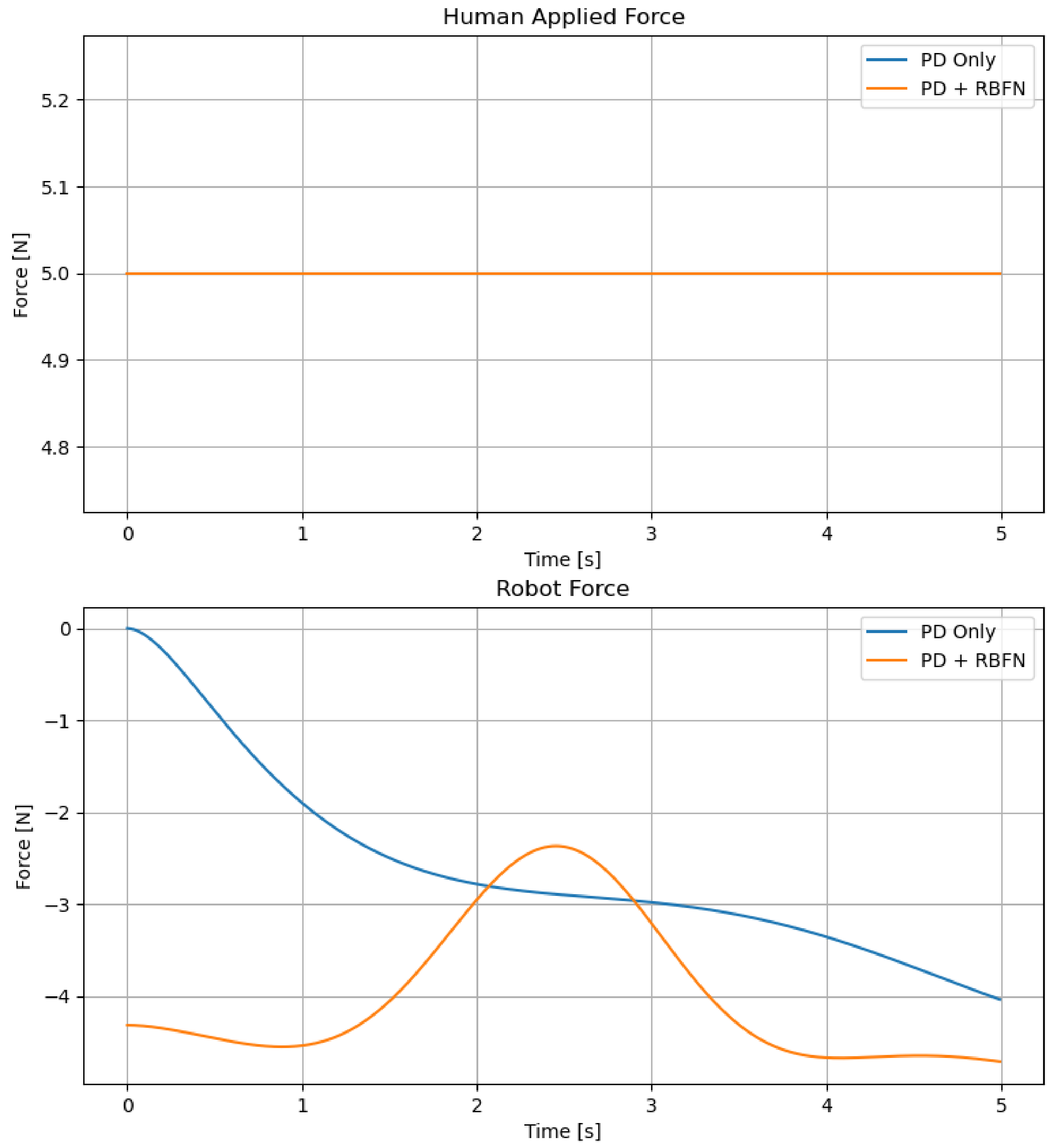


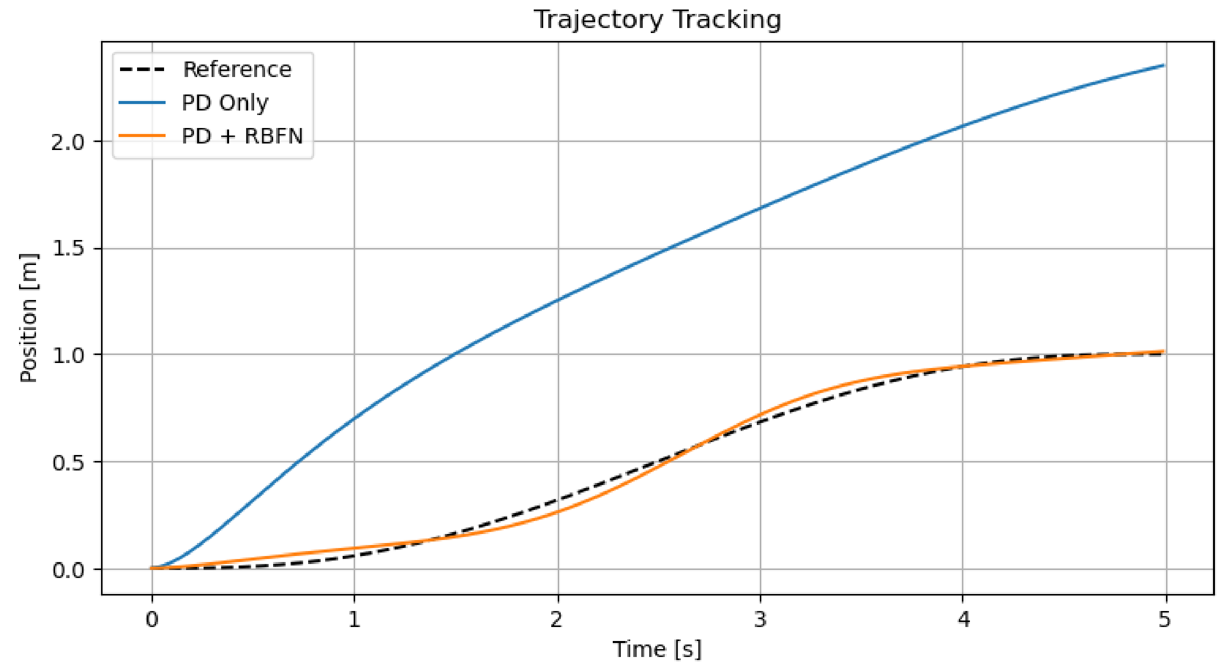
$$w_i \leftarrow w_i + \eta \cdot (x_{\text{ref}} - x) \cdot \phi_i(x_{\text{ref}}) \cdot dt$$

$$f_{\text{rbfn}} = \sum_{i=1}^{n} w_i \cdot \phi_i(x_{\text{ref}})$$


Human "A" Adaptation Progress
RBFN + PD Human Force
Human Force [N]
Time within Cycle [s]
RBFN + PD Trajectory Tracking
Position [m]
Time within Cycle [s]
RBFN + PD Force Profile
Robot Force [N]
Time within Cycle [s]
Cycle 1
Cycle 2
Cycle 3
Cycle 4
Cycle 5
Cycle 6
Cycle 7
Cycle 8
Cycle 9
Cycle 10
Reference

Human "B" Final Cycle Control Comparison

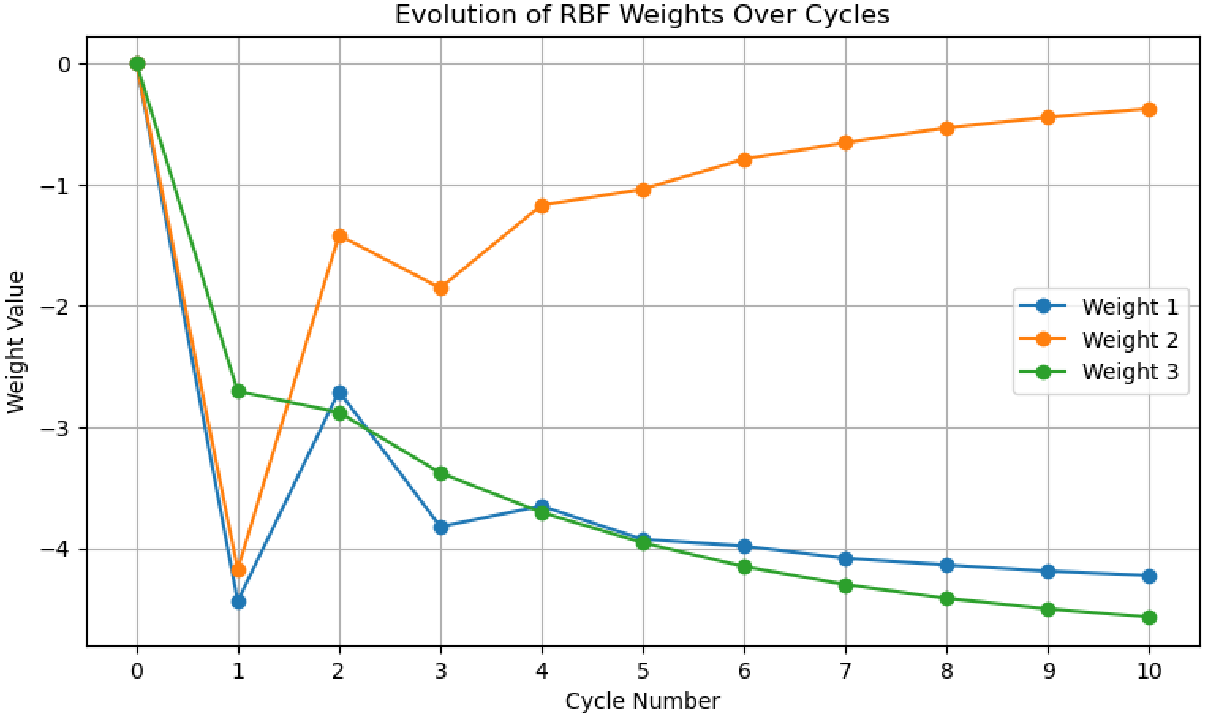


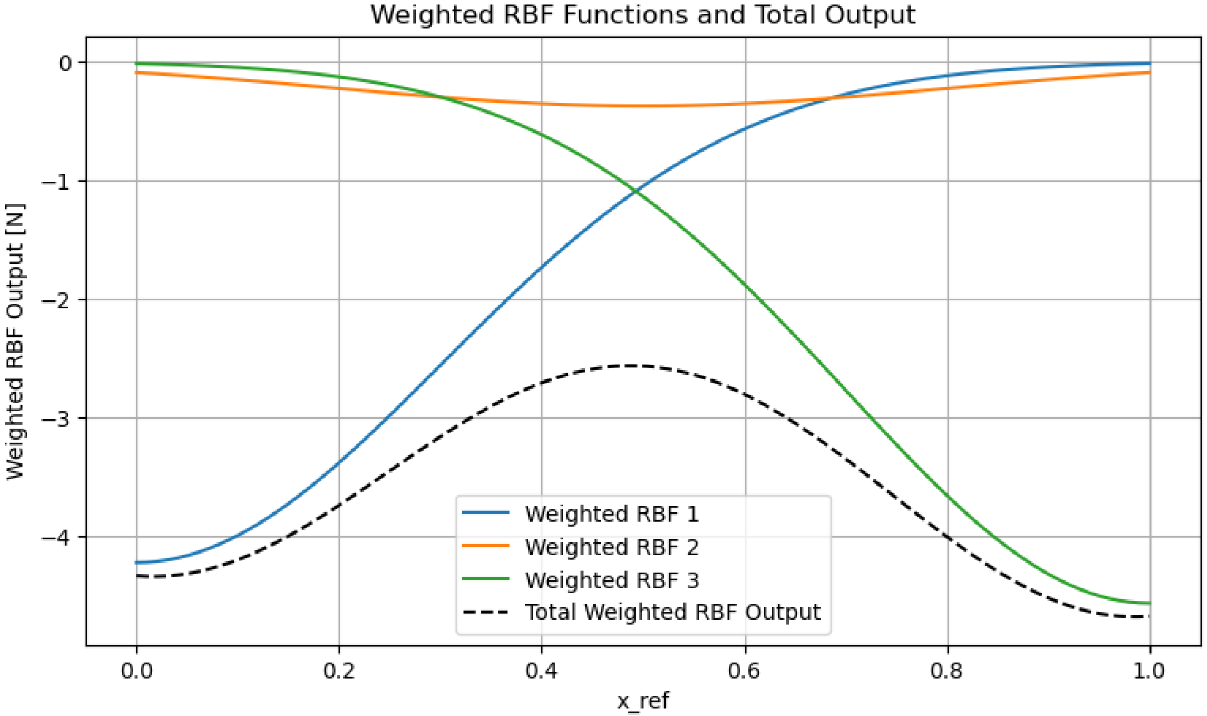


힘을 항상 5N을 내는 사람

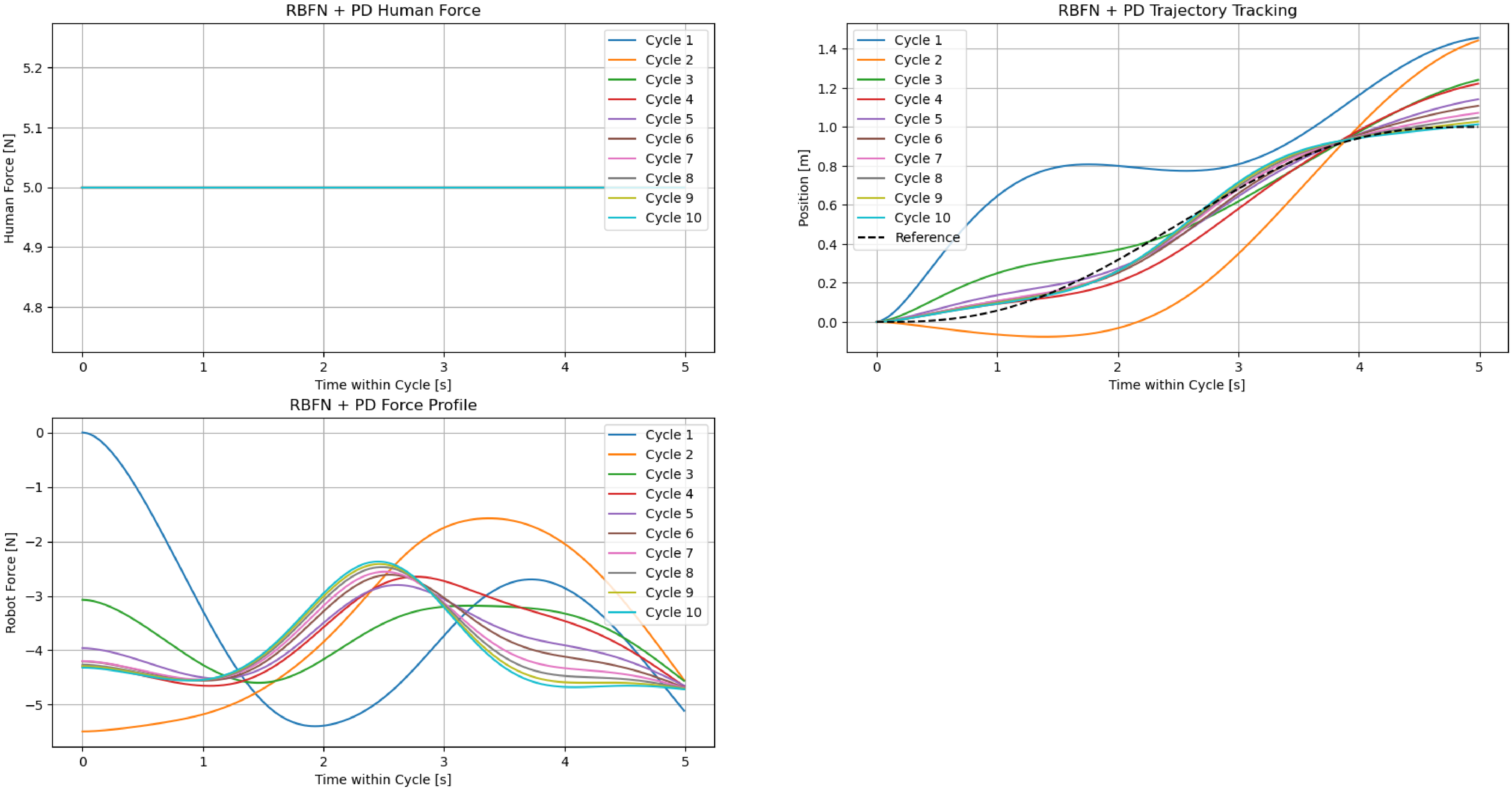
- RBFN이 궤적 tracking을 위해 resist 같은 역할을 함

Human "B" RBFN Weight

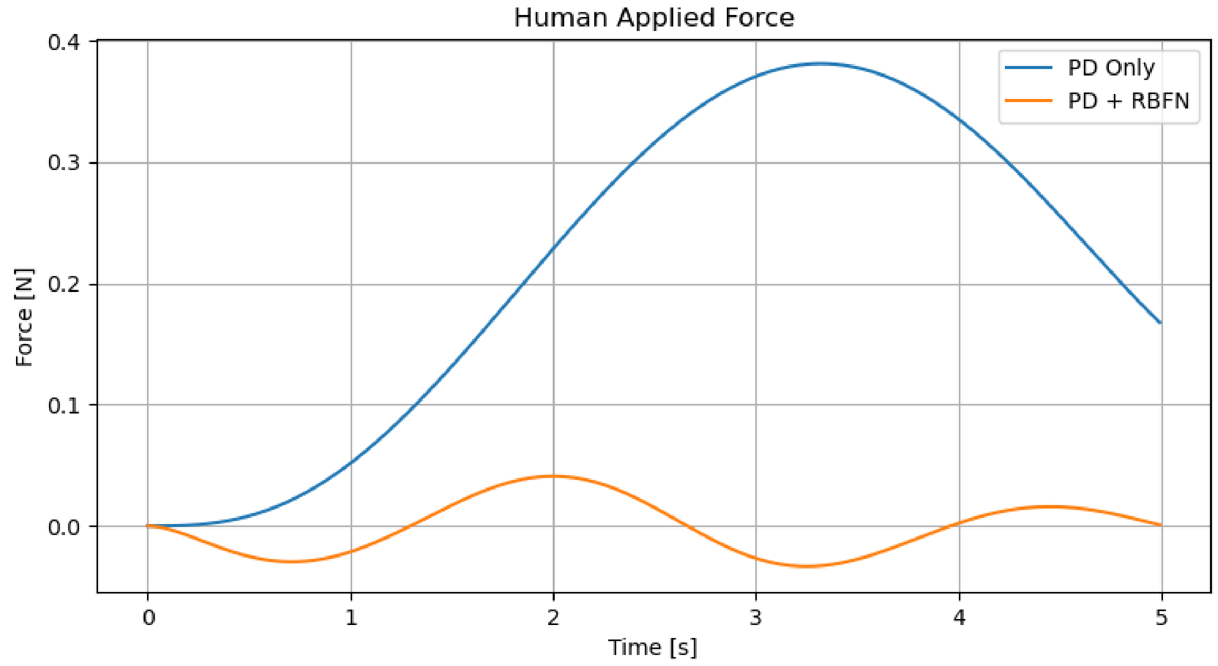


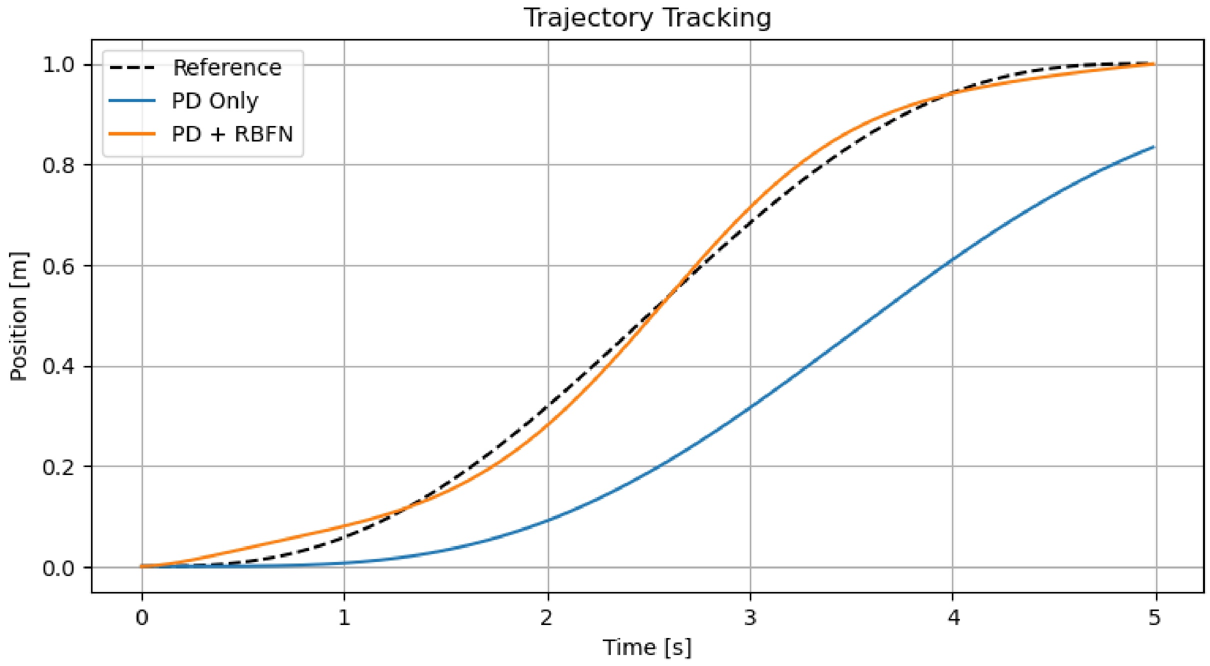


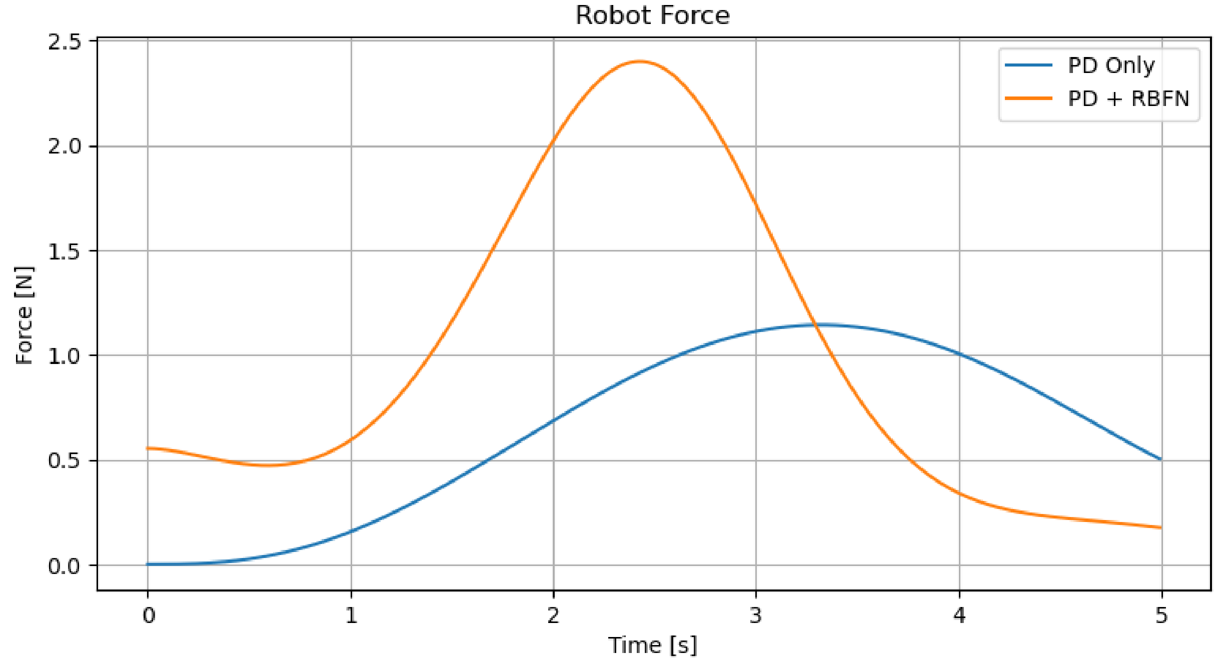
Human "B" Adaptation Progress



Human "C" Final Cycle Control Comparison

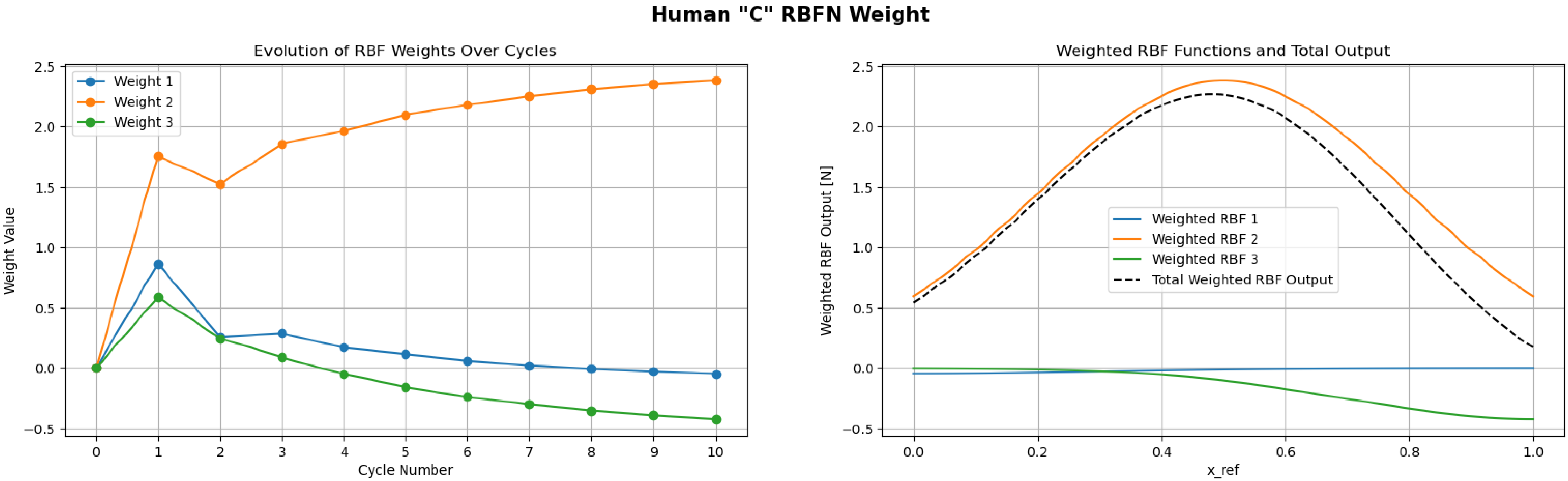




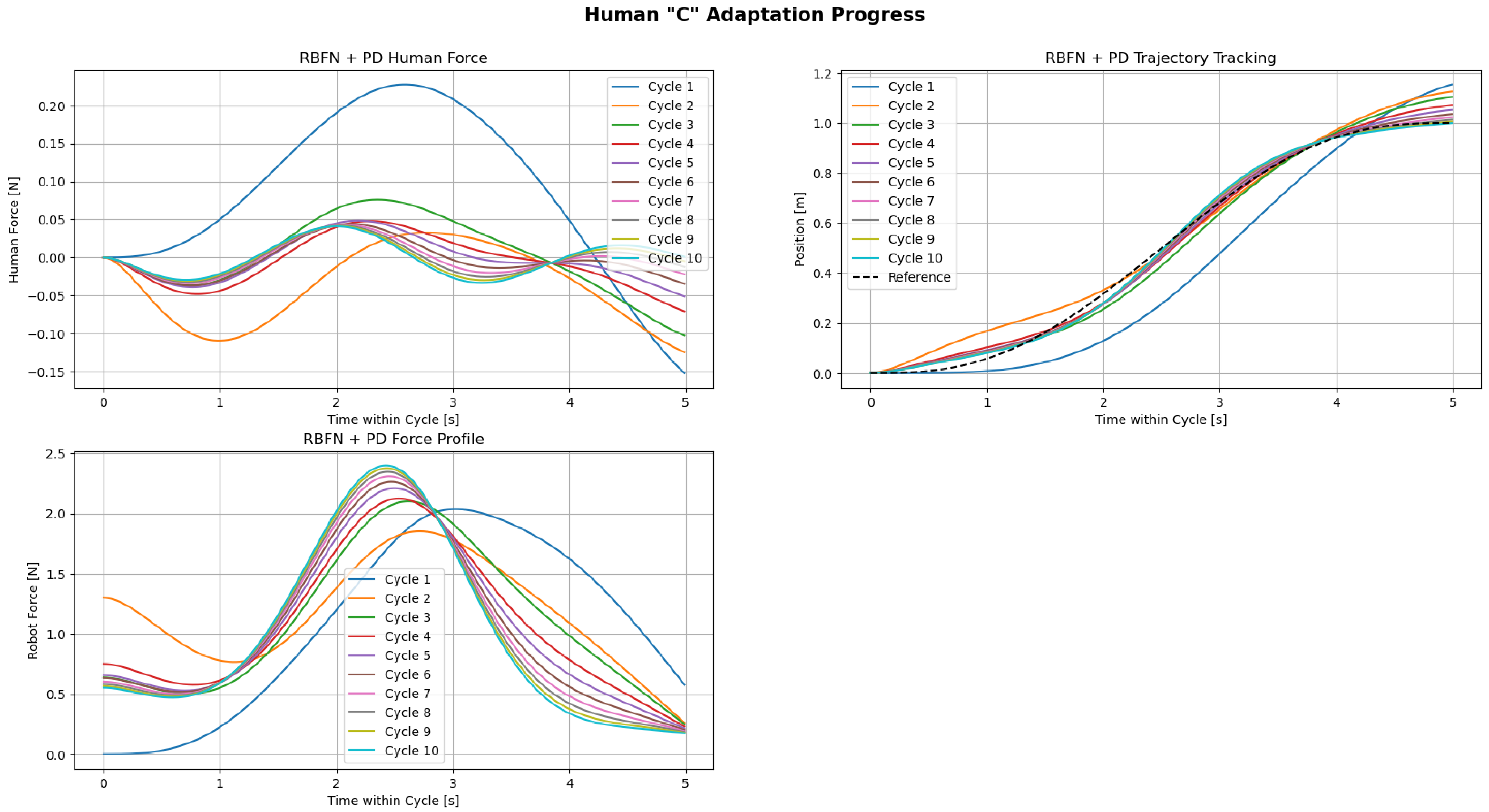


MCK중 K가 작은 사람

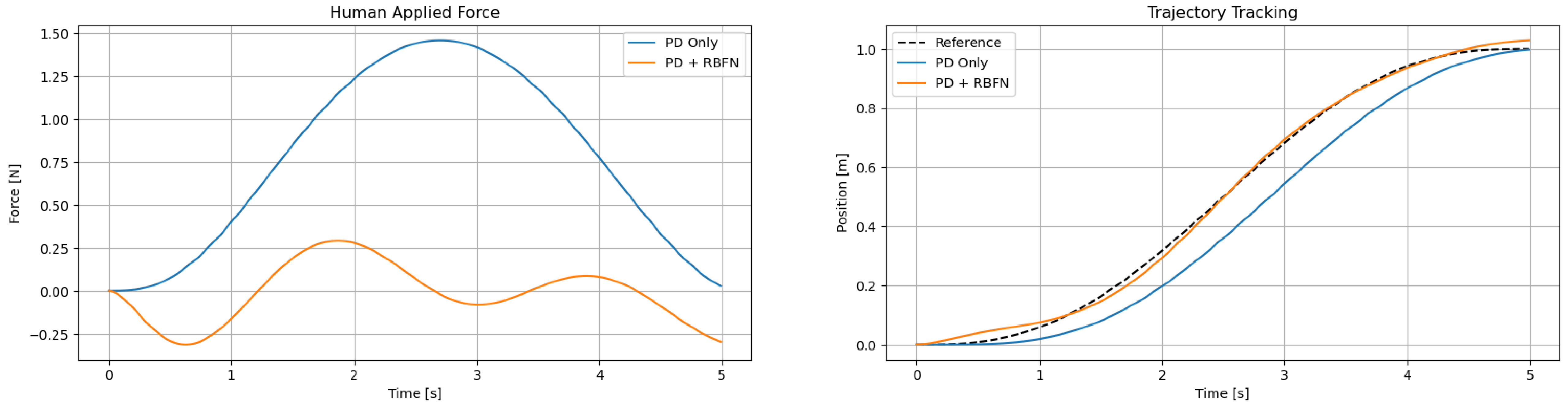
- RBFN이 좋은 성능을 냄
- 대신 에러가 줄어들면서 사람이 내는 힘도 줄어듬

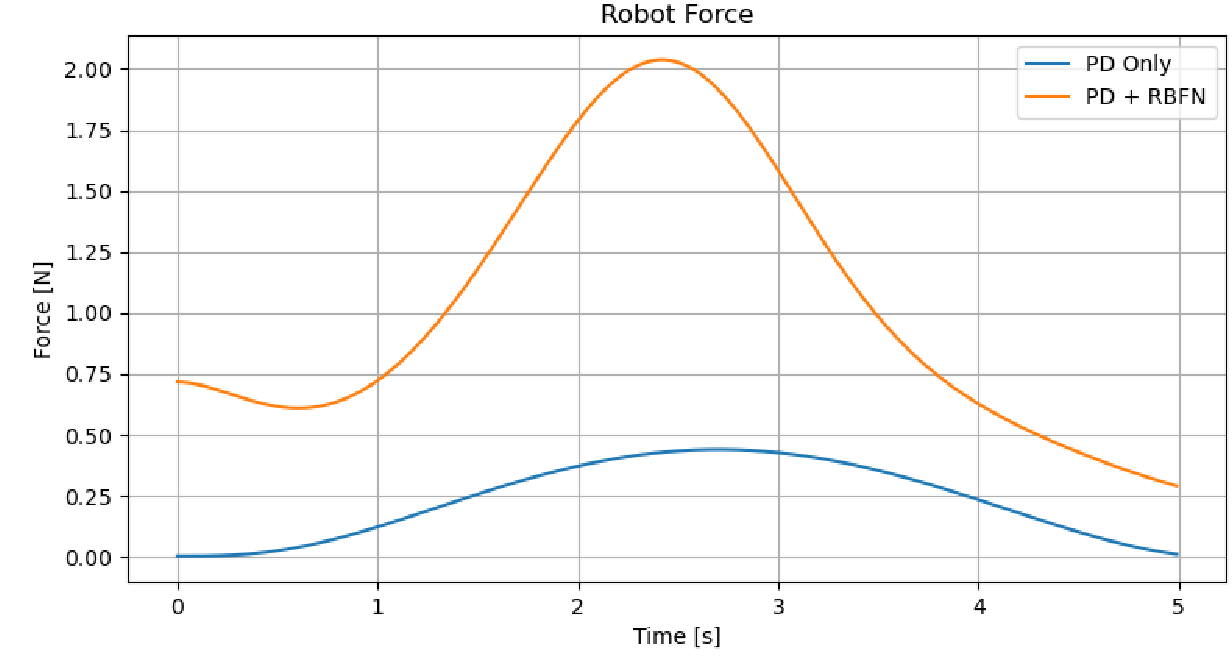


Human "C" RBFN Weight
Evolution of RBF Weights Over Cycles
Weight 1
Weight 2
Weight 3
Weight Value
Cycle Number
2.5
2.0
1.5
1.0
0.5
0.0
−0.5
0
1
2
3
4
5
6
7
8
9
10
Weighted RBF Functions and Total Output
Weighted RBF 1
Weighted RBF 2
Weighted RBF 3
Total Weighted RBF Output
Weighted RBF Output [N]
x_ref
0.0
0.2
0.4
0.6
0.8
1.0


Human "C" Adaptation Progress
RBFN + PD Human Force
Human Force [N]
Time within Cycle [s]
RBFN + PD Trajectory Tracking
Position [m]
Time within Cycle [s]
Reference
RBFN + PD Force Profile
Robot Force [N]
Time within Cycle [s]
Cycle 1
Cycle 2
Cycle 3
Cycle 4
Cycle 5
Cycle 6
Cycle 7
Cycle 8
Cycle 9
Cycle 10

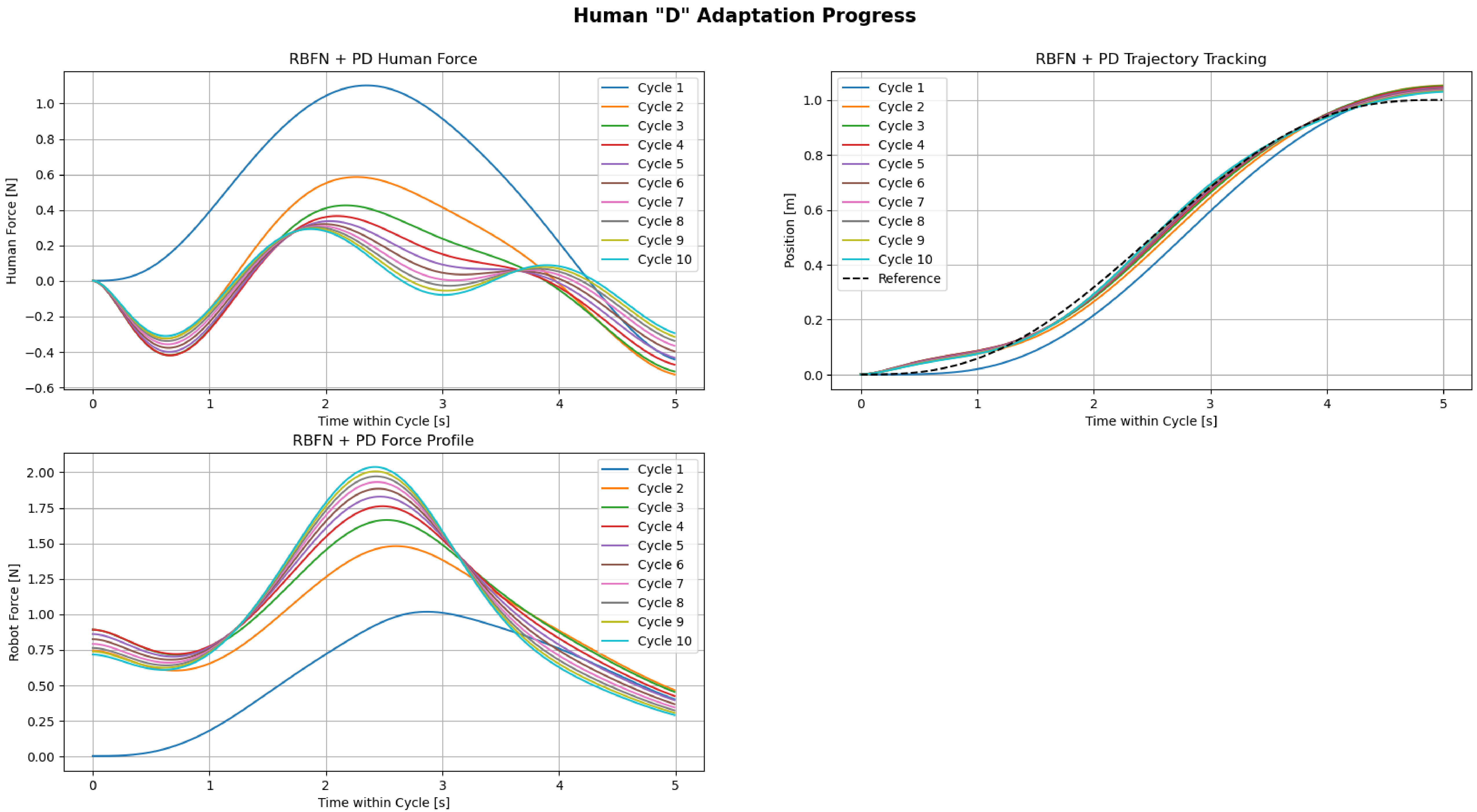
Human "D" Final Cycle Control Comparison



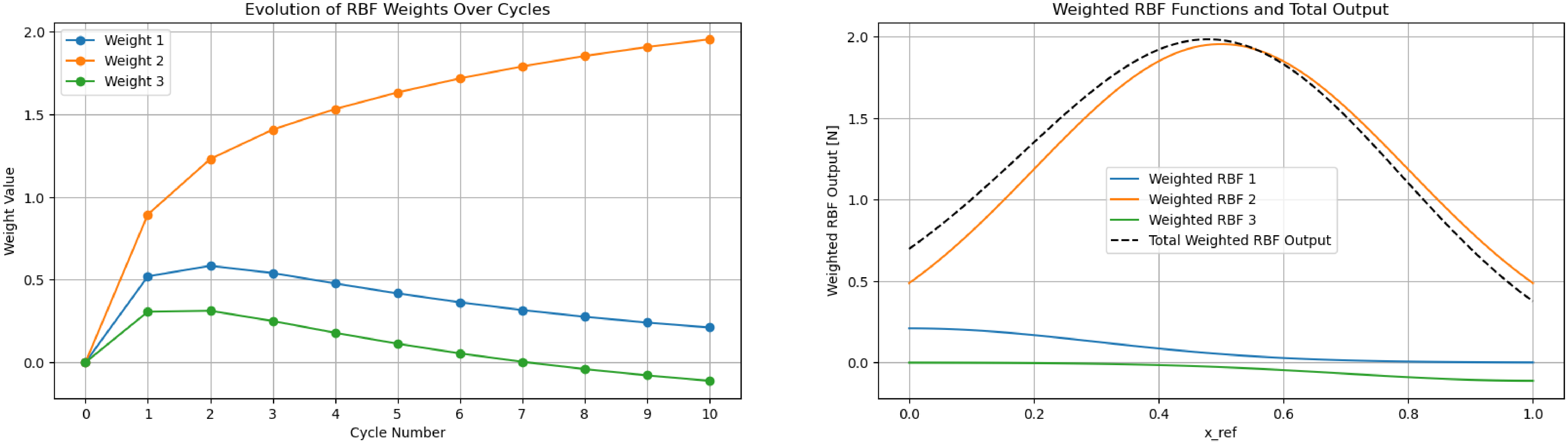


MCK중 K가 큰 사람

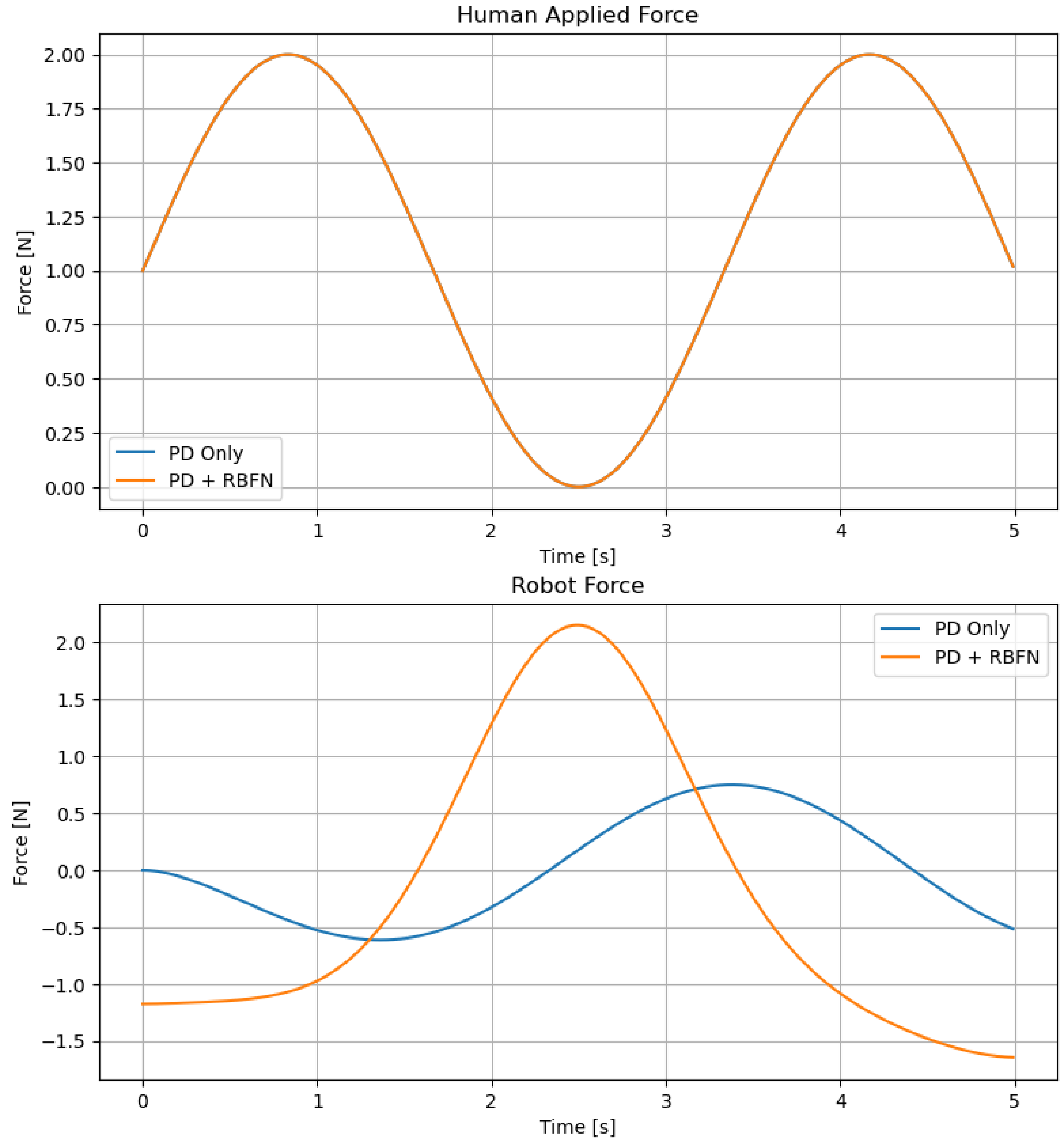
- RBFN이 좋은 성능을 냄

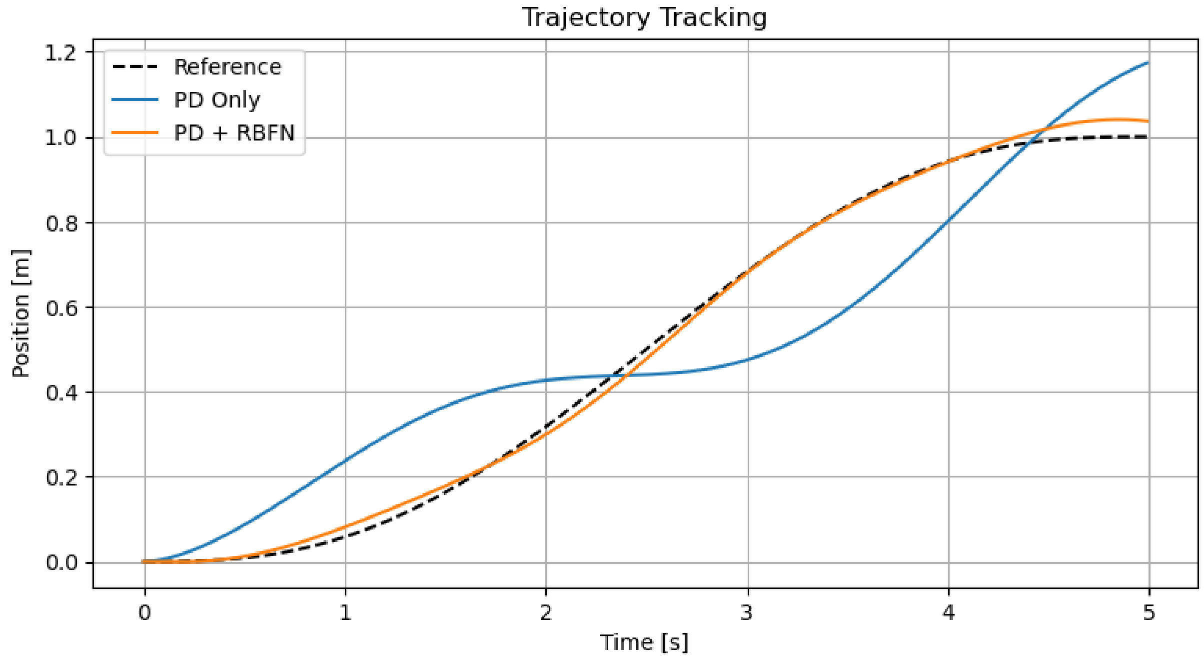

Human "D" Adaptation Progress
RBFN + PD Human Force
Human Force [N]
Time within Cycle [s]
RBFN + PD Trajectory Tracking
Position [m]
Time within Cycle [s]
RBFN + PD Force Profile
Robot Force [N]
Time within Cycle [s]
Cycle 1
Cycle 2
Cycle 3
Cycle 4
Cycle 5
Cycle 6
Cycle 7
Cycle 8
Cycle 9
Cycle 10
Reference

Human "D" RBFN Weight



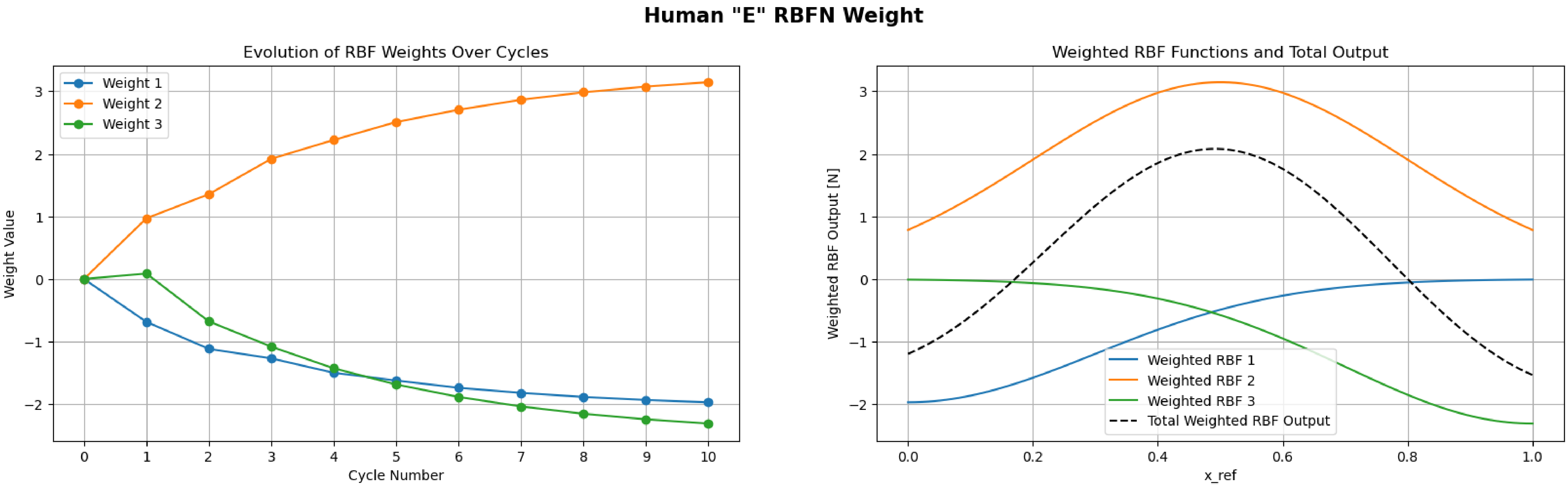
Human "E" Final Cycle Control Comparison

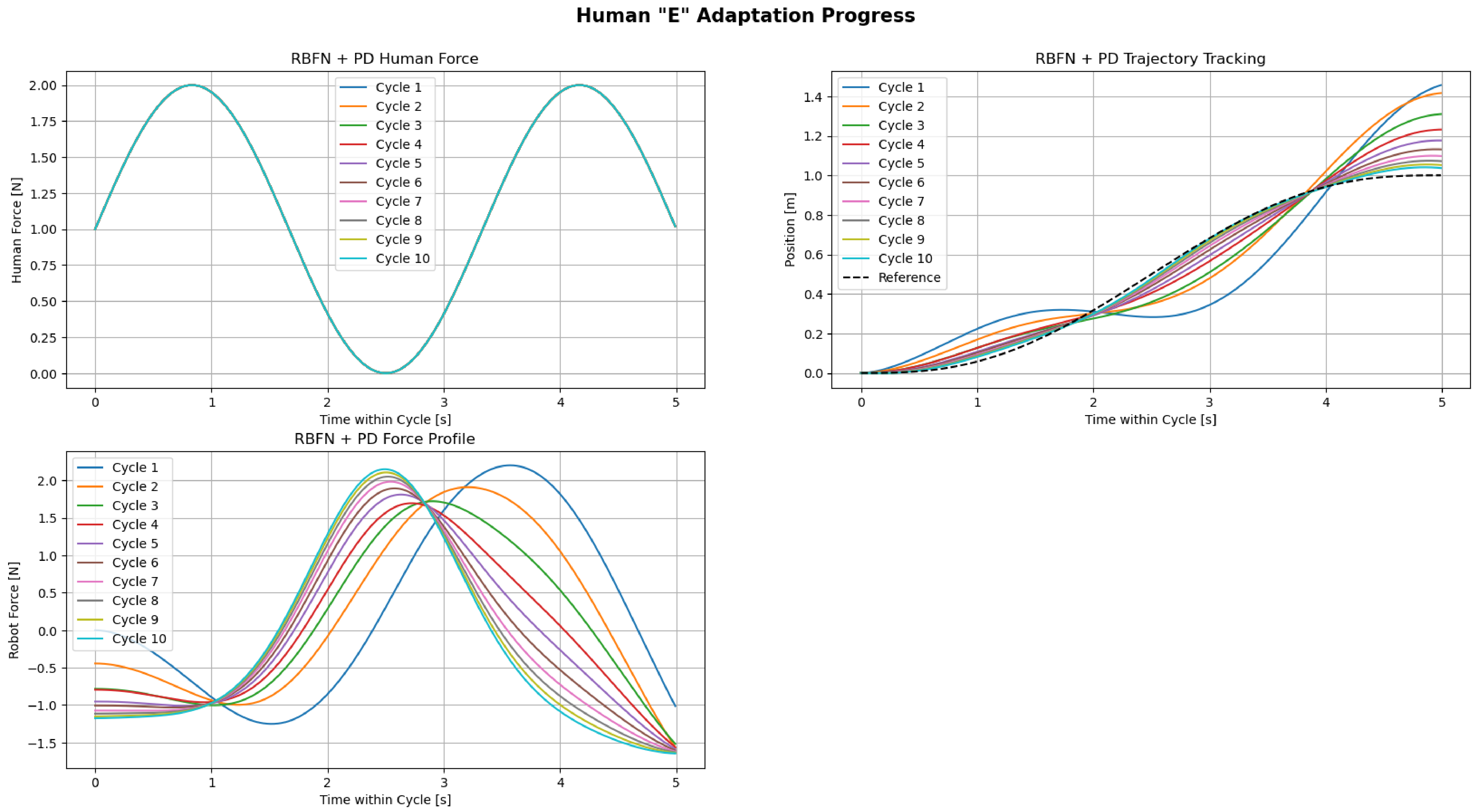




이상한 사람

- 초반과 마지막만 힘을 주는 사람
- RBFN이 좋은 성능을 냄


Human "E" RBFN Weight
Evolution of RBF Weights Over Cycles
Weight 1
Weight 2
Weight 3
Weight Value
Cycle Number
Weighted RBF Functions and Total Output
Weighted RBF 1
Weighted RBF 2
Weighted RBF 3
Total Weighted RBF Output
Weighted RBF Output [N]
x_ref



Human "E" Adaptation Progress
RBFN + PD Human Force
Human Force [N]
Time within Cycle [s]
RBFN + PD Trajectory Tracking
Position [m]
Time within Cycle [s]
Reference
RBFN + PD Force Profile
Robot Force [N]
Time within Cycle [s]
Cycle 1
Cycle 2
Cycle 3
Cycle 4
Cycle 5
Cycle 6
Cycle 7
Cycle 8
Cycle 9
Cycle 10

정리

RBFN는 ref궤적을 잘 따라가는 역할을 해준다.

논제 : ref궤적보다 앞서면 반대 방향으로 힘을 주어 궤적을 잘 따라가게 해주는데 이것을 resist 라고 할 수 있을까?

질문1 : PID는 왜 들어갔는가?

시뮬레이션에서는 RBFN이면 충분히 ref궤적을 트래킹할테지만

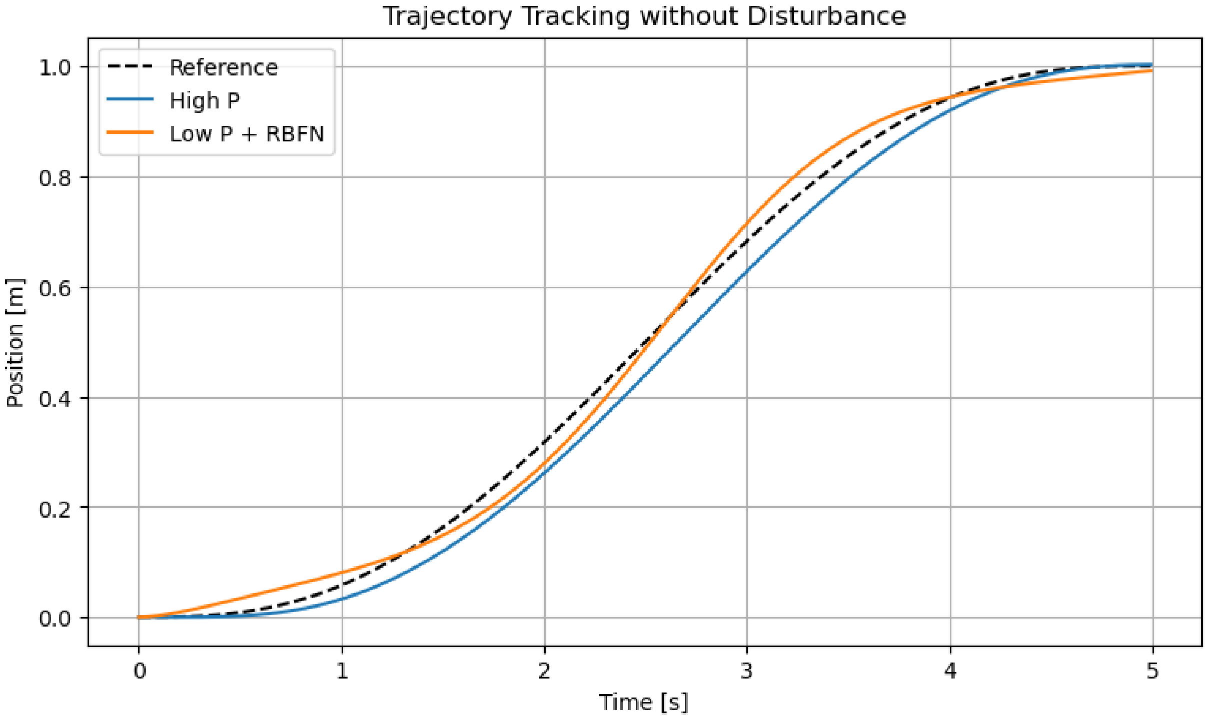
실제 상황에서는 모델링 오차가 있기 때문에 낮은 P게인 제어를 추가된다.

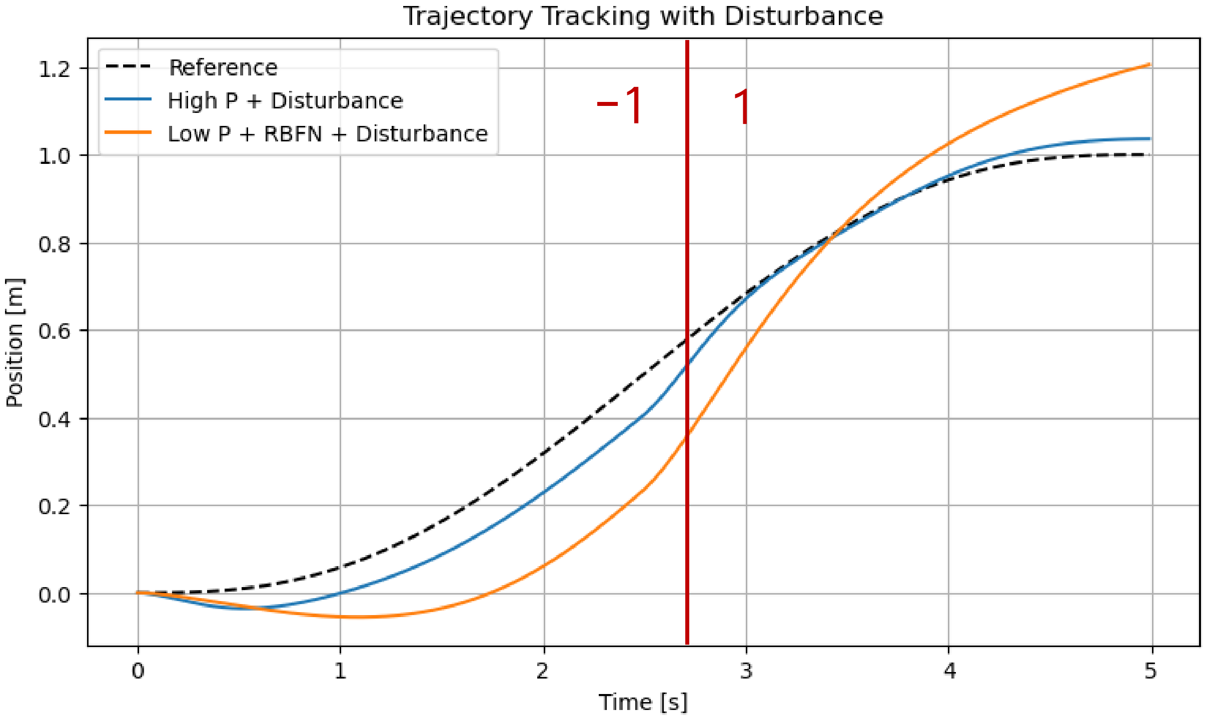
정리

질문2 : 반대로 PID만 써도 궤적 트래킹은 가능하다?

궤적 트래킹을 위해서는 높은 P게인이 필요하다. P게인이 커지면 Stiffness가 커지고, Compliance가 떨어진다. (아래 예시 High P : 30, Low P : 3)

“a stiff controller can complete the movements without active participation from the patient, which may limit the therapeutic effect of the training”





정리

질문3 : Compliance만 보장해도 맞춤형이라고 얘기할 수 있을까?

궤적을 잘 트레킹하더라도 사용자의 퍼포먼스에 기반하여 난이도를 더 높여줄 필요성이 있다.

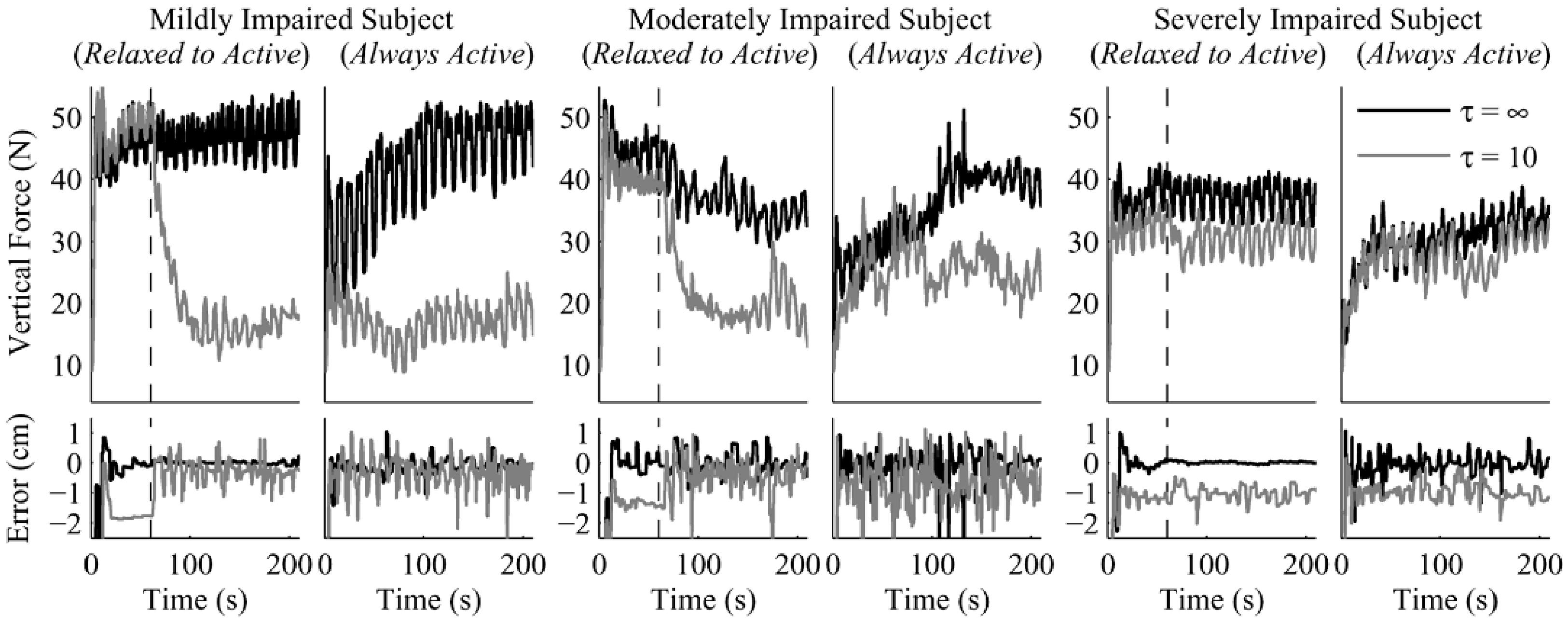


Fig. 5. Vertical assistance force and vertical tracking error during the *side-to-side* experiment for subjects with mild ($\mathrm{FM} = 53$, left main column), moderate ($\mathrm{FM} = 30$, center main column), and severe ($\mathrm{FM} = 16$, right main column) impairment. Each main column shows results from a single subject for both *relaxed to active* (left subcolumn) and *always active* (right subcolumn) conditions. Dotted line marks the end of the fifth side to side movement for the *relaxed to active* condition.

최적화

사람의 힘을 적극적으로 개입하게 하려면 추가적인 기법이 필요하다. ➡ Fine Tuning

방법1 : Forgetting Factor

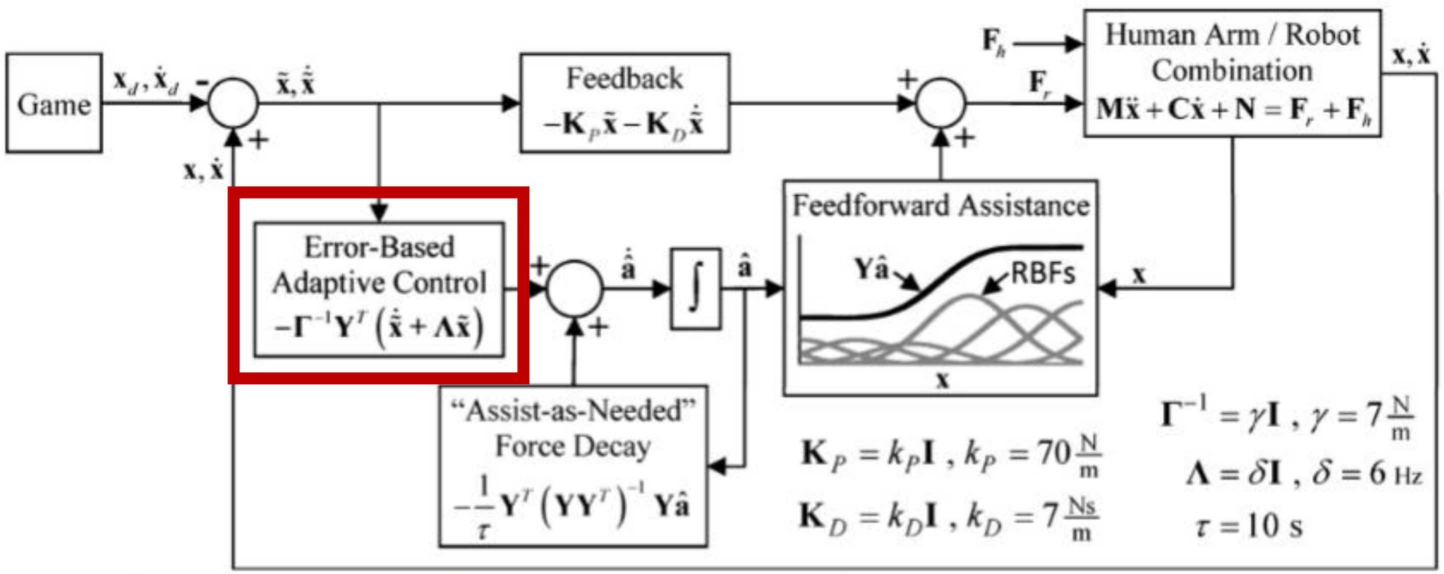


Fig. 2. Controller diagram. The "assist-as-needed" force decay term continuously reduces the feedforward assistance when errors are small. Feedforward assistance is a learned model of the subject's abilities and effort using radial basis functions. Gains of the controller are given in the figure. The effective integral, proportional, and derivative gains, taking into account the adaptive action of the controller, are derived in the Appendix.

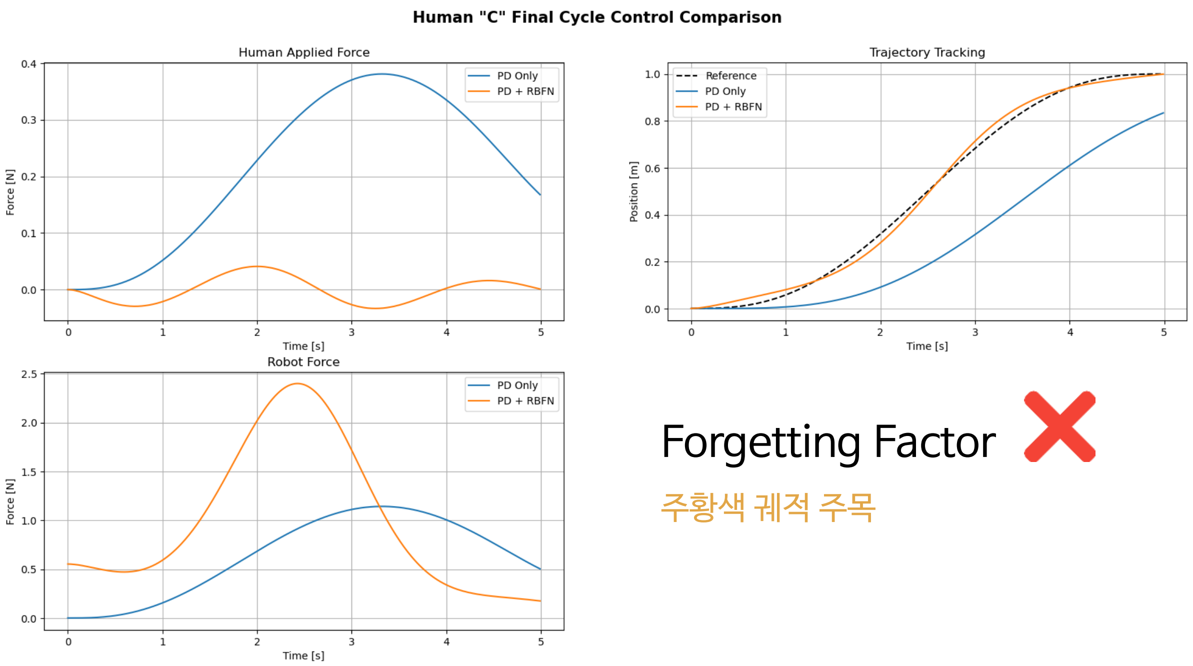
Lyapunov-based

$$\dot{\hat{\mathbf{a}}} = -\frac{1}{\tau}\mathbf{Y}^T\left(\mathbf{Y}\mathbf{Y}^T\right)^{-1}\mathbf{Y}\hat{\mathbf{a}}.$$

SGD

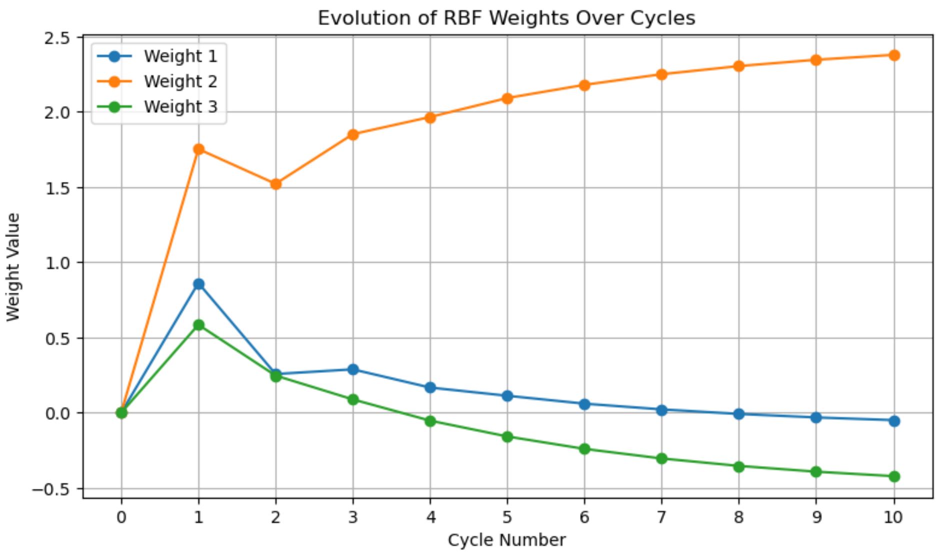
0.999

$$w_i \leftarrow \lambda w_i + \eta \cdot (x_{\mathrm{ref}} - x) \cdot \phi_i(x_{\mathrm{ref}}) \cdot dt$$

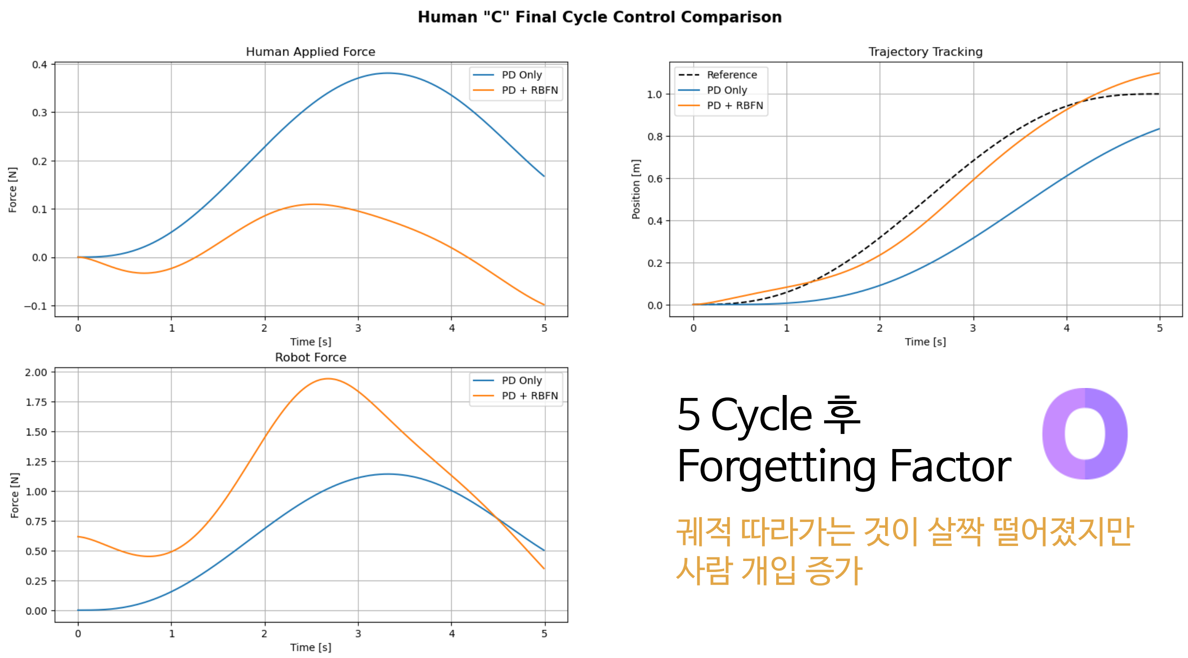


Forgetting Factor ❌

주황색 궤적 주목

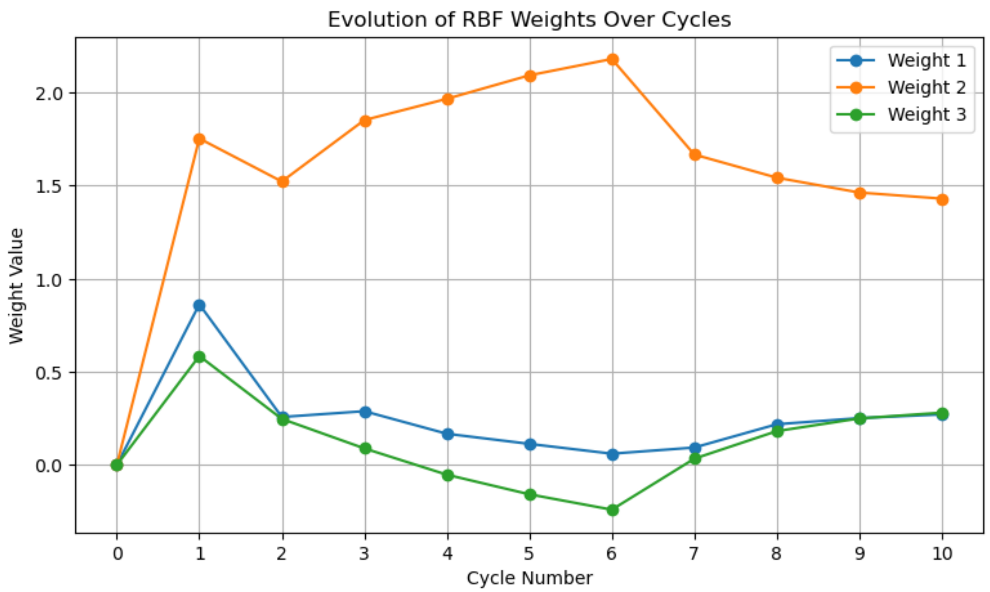


MCK중 K가 작은 사람



5 Cycle 후
Forgetting Factor O

궤적 따라가는 것이 살짝 떨어졌지만
사람 개입 증가



최적화

Forgetting Factor의 문제점?

1. 앞서나가는 것을 억제하는 힘을 resist라고 인정했을때, 해당하는 resist 힘조차 forget 해버린다.
2. 저게 정말 환자에 최적화된 힘이 맞는가?

$$\boxed{f_{\text{resist}} = \sum_i w_{\text{resist},i}\phi_i}$$

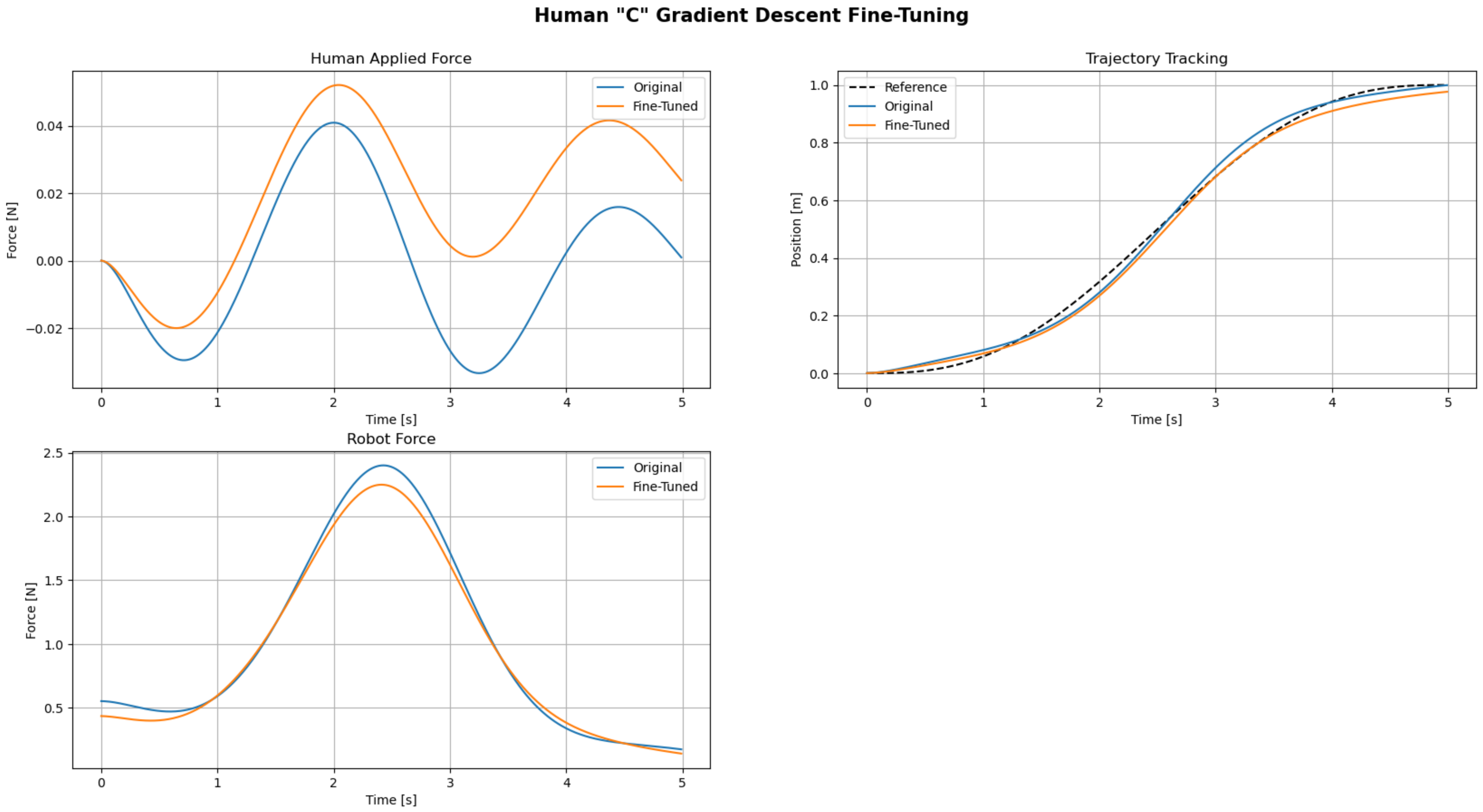
Cost Function 정의

$$J = W_1(f_{\text{assist}} + f_{\text{resist}}) + W_2e^2$$

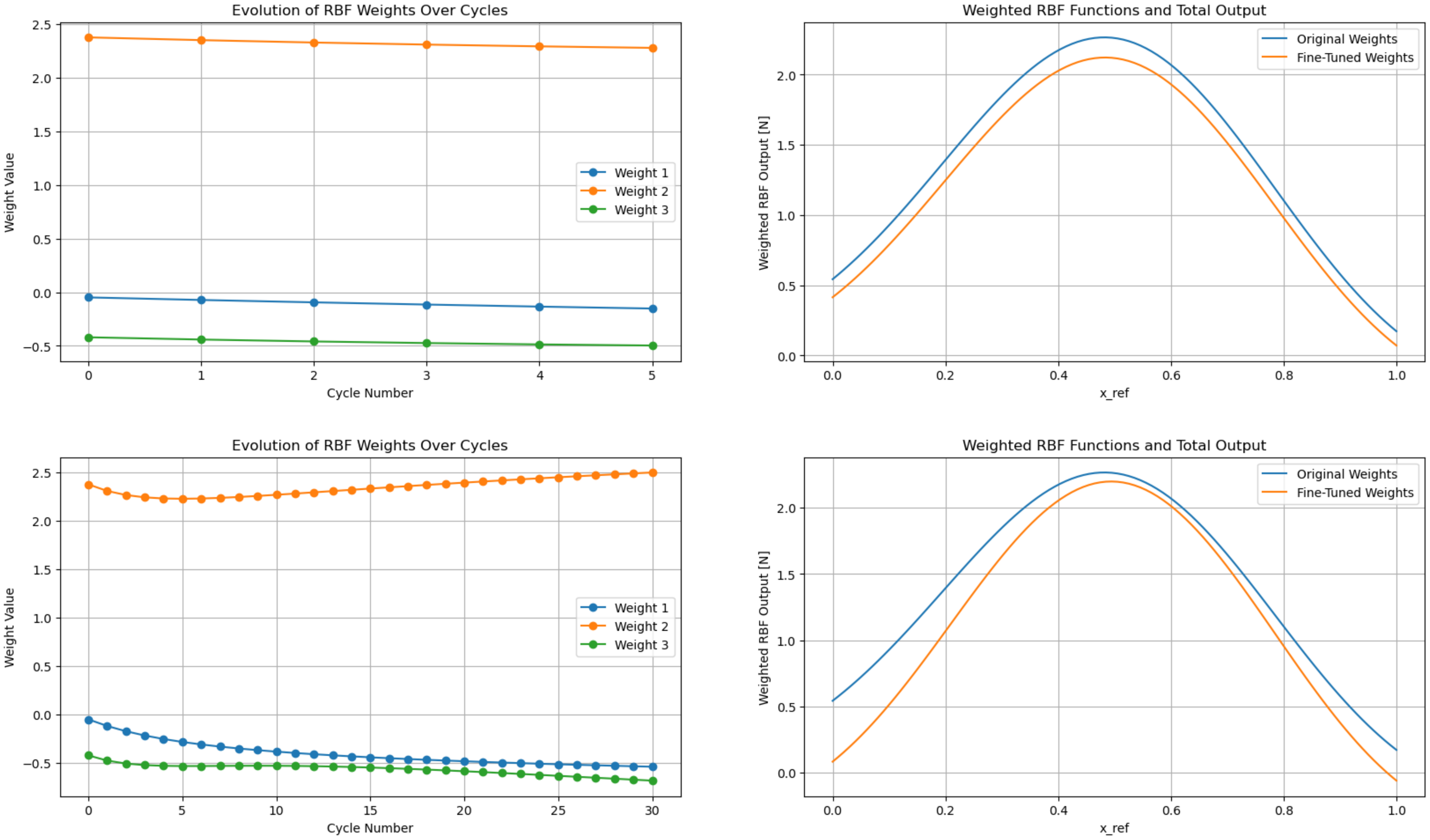
SGD

$$w_{\text{resist},i} \leftarrow w_{\text{resist},i} - \eta_{\text{resist}} \frac{\partial J}{\partial w_{\text{resist},i}}$$

$$\frac{\partial J}{\partial w_{\text{resist},i}} = (W_1 - 2W_2edt)\,\phi_i$$



Human "C" Gradient Descent Fine-Tuning
Human Applied Force
Force [N]
Time [s]
Original
Fine-Tuned
Trajectory Tracking
Position [m]
Time [s]
Reference
Original
Fine-Tuned
Robot Force
Force [N]
Time [s]
Original
Fine-Tuned


Evolution of RBF Weights Over Cycles
Weight Value
Cycle Number
Weight 1
Weight 2
Weight 3
Weighted RBF Functions and Total Output
Weighted RBF Output [N]
x_ref
Original Weights
Fine-Tuned Weights
Evolution of RBF Weights Over Cycles
Weight Value
Cycle Number
Weight 1
Weight 2
Weight 3
Weighted RBF Functions and Total Output
Weighted RBF Output [N]
x_ref
Original Weights
Fine-Tuned Weights

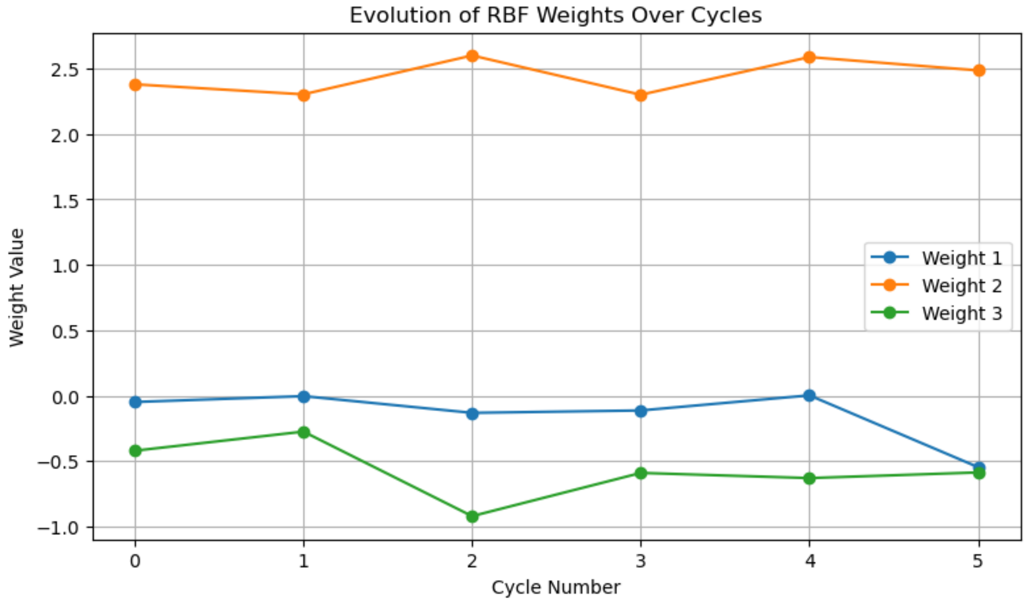
최적화

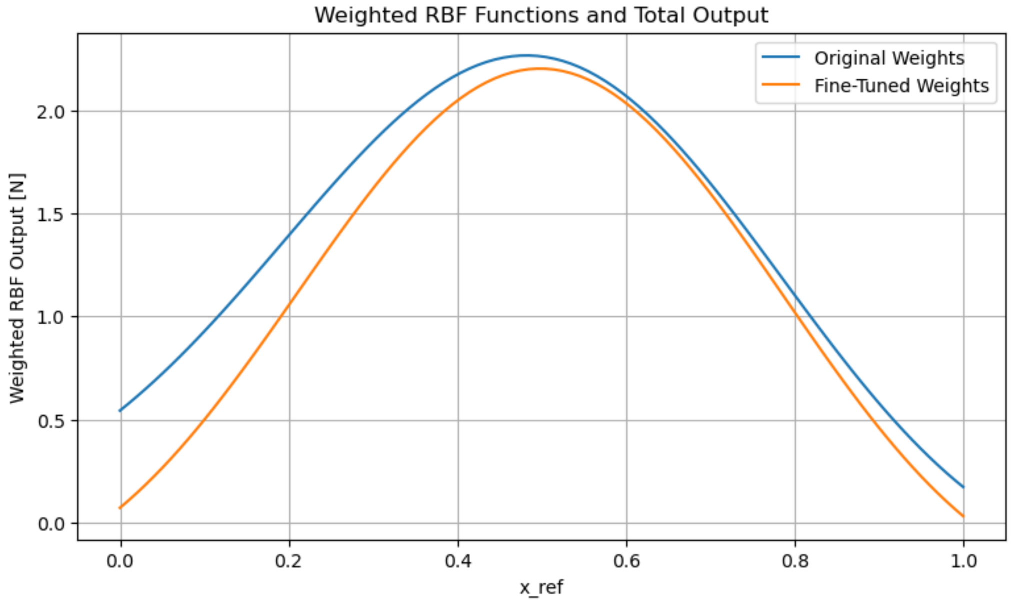
SGD의 문제점?

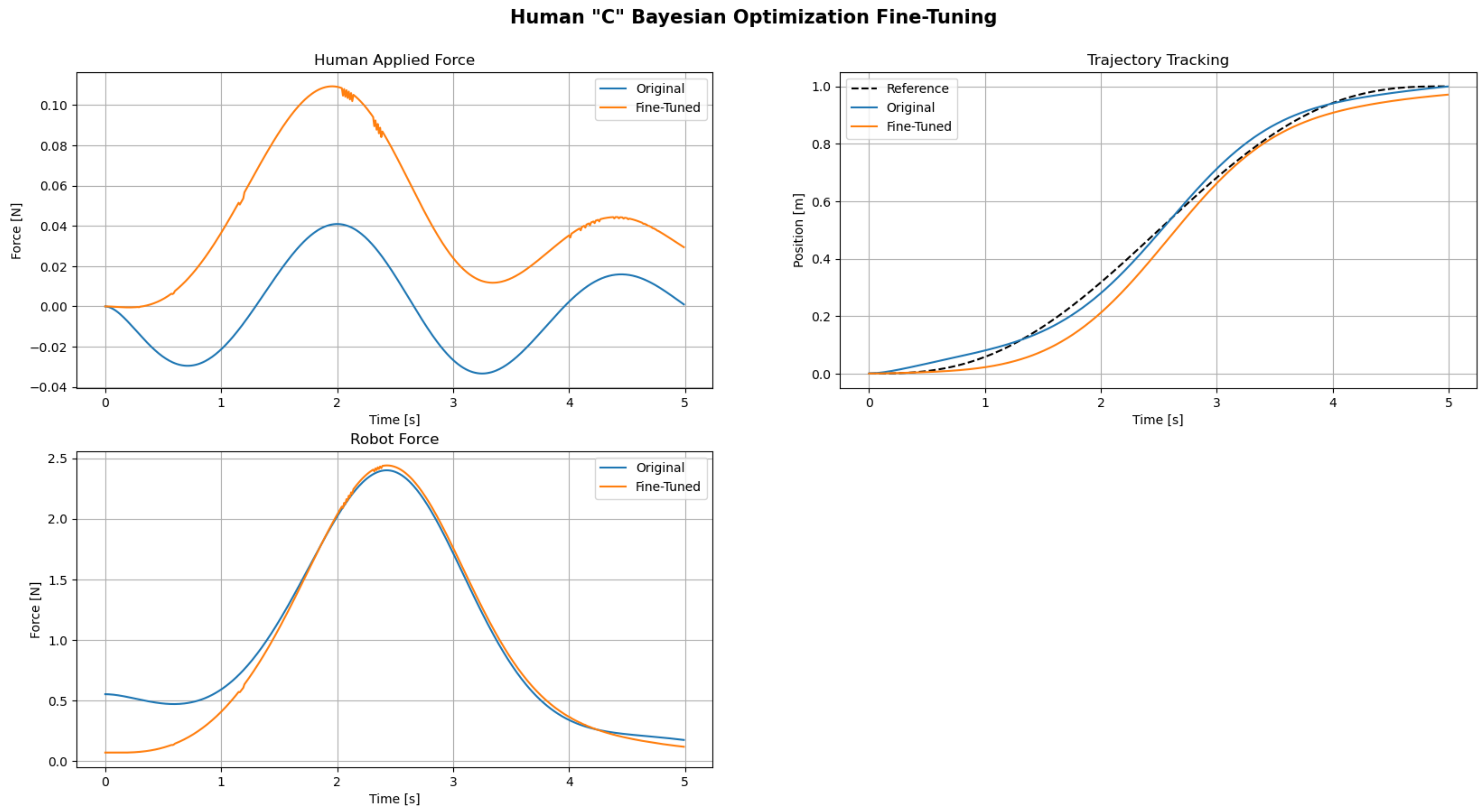
1. 많은 데이터 샘플이 필요하기 때문에 온라인을 학습을 해야 한다.

   만약 사이클이 끝나고 batch로 학습하면 위치에 대한 정보가 없어서 최적화가 되지 않는다.
2. Local minimum에 빠질 수 있다.

-〉 베이지안 최적화를 한다.







Human "C" Bayesian Optimization Fine-Tuning
Human Applied Force
Force [N]
Time [s]
Original
Fine-Tuned
0.10
0.08
0.06
0.04
0.02
0.00
−0.02
−0.04
Trajectory Tracking
Position [m]
Reference
Original
Fine-Tuned
1.0
0.8
0.6
0.4
0.2
0.0
Time [s]
Robot Force
Force [N]
Original
Fine-Tuned
2.5
2.0
1.5
1.0
0.5
0.0
0
1
2
3
4
5
Time [s]