Bioinspired Composite Learning Control
Under Discontinuous Friction for
Industrial Robots

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Abstract: Adaptive control can be applied to robotic systems with parameter uncertainties, but
improving its performance is usually difficult, especially under discontinuous friction. Inspired by
the human motor learning control mechanism, an adaptive learning control approach is proposed
for a broad class of robotic systems with discontinuous friction, where a composite error learning
technique that exploits data memory is employed to enhance parameter estimation. Compared
with the classical feedback error learning control, the proposed approach can achieve superior
transient and steady-state tracking without high-gain feedback and persistent excitation at the
cost of extra computational burden and memory usage. The performance improvement of the
proposed approach has been verified by experiments based on a DENSO industrial robot.

Keywords: Robot control, Adaptive control, discontinuous friction, data memory, feedback
error learning, parameter learning.

1. INTRODUCTION
The feedback error learning (FEL) framework is a com-
putational model of human motor learning control in the cere-
bellum, where the limitations on feedback delays and small
feedback gains in biological systems can be overcome by
internal forward and inverse models, respectively (Kawato
et al., 1988). The name “FEL” emphasizes the usage of
a feedback control signal for the heterosynaptic learning
of internal neural models. There are two key features for
the FEL: Internal dynamics modeling and hybrid feedback-
feedforward (HFF) control, which are well supported by
much neuroscientific evidence (Thoroughman et al., 2000;
Wolpert et al., 1998; Morasso et al., 2005).

A simplified FEL architecture without the internal for-
ward model has been extensively studied for robot control
(Kawato et al., 1988; Tolu et al., 2012; Gomi et al., 1993;
Hamavand et al., 1995; Talebi et al., 1998; Topalov et
al., 1998; Teshnehlab et al., 1996; Kalanovic et al., 2000;
Kurosawa et al., 2005; Neto et al., 2010; Jo et al., 2011).
However, stability guarantee relies on a precondition that
the controlled plant can be stabilized by linear feedback
without feedforward control in Tolu et al. (2012); Kawato
et al. (1988); Teshnehlab et al. (1996); Kalanovic et al.
(2000); Kurosawa et al. (2005); Neto et al. (2010); Jo et al.
(2011), which may not be satisfied for many control prob-
lems such as robot tracking control; in Gomi et al. (1993);
Hamavand et al. (1995); Talebi et al. (1998); Topalov et
al. (1998), internal inverse models are implemented in the
feedback loops, which violates the original motivation of
proposing FEL. Stability analysis of FEL control for a
class of nonlinear systems was investigated in Nakanishi
et al. (2004), where the feedback gain is required to be
sufficiently large to compensate for plant uncertainty so
as to guarantee closed-loop stability. The approach of
Nakanishi et al. (2004) was applied to the rehabilitation of
Parkinson’s disease in Rouhollahi et al. (2017). However,
the accurate capture of the plant dynamics is not fully
investigated and discontinuous friction is largely neglected
in existing FEL robot control methods.

This paper proposes a bioinspired adaptive learning con-
trol approach for a broad class of robotic systems with
discontinuous friction, where a composite error learning
(CEL) technique exploiting data memory is applied to en-
hance parameter estimation. The word “composite” refers
to the composite exploitation of instantaneous data and
data memory, and the composite exploitation of the track-
ing error and a generalized predictive error for parameter
learning. Compared with the classical FEL control, the
proposed approach can achieve superior transient and
steady-state tracking without high-gain feedback and per-
The FEL control process for human voluntary movements (Sadegh et al., 1990): 1) The regressor output can be calculated and stored offline to significantly reduce the amount of online calculations; 2) the noise correlation between the parameter estimation error in the parameter update law and the adaptation signal (i.e., an infinite gain phenomenon) can be removed to enhance estimation robustness. Additional advantages of HFF control based on neural networks can be referred to Pan et al. (2016a, 2017a). This study is based on our previous studies in composite learning control (Pan et al., 2016b,c, 2017b, 2018, 2019; Guo et al., 2019, 2020, 2022a,b), in which the methods of Pan et al. (2016b,c, 2018, 2019) do not consider discontinuous friction, the methods of Pan et al. (2016b,c, 2017b) consider only the case of $M(q)$ in (1) being a known constant, and all the above methods do not resort to the HFF scheme.

In the rest of this article, the control problem is formulated in Sec. 3; the CEL control is presented in Sec. 4; experimental results are given in Sec. 5; conclusions are drawn in Sec. 6. Throughout this paper, $\mathbb{R}$, $\mathbb{R}^+$, $\mathbb{R}^n$ and $\mathbb{R}^{n \times m}$ denote the spaces of real numbers, positive real numbers, real $n$-vectors and real $n \times m$-matrices, respectively, $\|x\|$ denotes the Euclidean norm of $x$, $L_n$ denotes the space of bounded signals, $\text{tr}(A)$ denotes the trace of $A$, $\lambda_{\min}(A)$ denotes the minimal eigenvalue of $A$, diag($\cdot$) denotes a diagonal matrix, $\text{min}(-)$, $\text{max}(-)$ and $\text{sup}(\cdot)$ denote the operators of minimum, maximum and supremum, respectively, $B_c := \{x|\|x\| \leq c\}$ is the ball of radius $c$, and $C^k$ represents the space of functions whose $k$-order derivatives all exist and are continuous, where $c \in \mathbb{R}^+$, $x \in \mathbb{R}^n$, $A \in \mathbb{R}^{n \times n}$, and $n$, $m$ and $k$ are natural numbers. In the subsequent sections, for the sake of brevity, the argument(s) of a function may be omitted while the context is sufficiently explicit.

2. BIOLOGICAL BACKGROUND

The FEL control process for human voluntary movements is described following the procedure (Wolpert et al., 1998):

1. The association cortex sends a desired output $q_d$ to the motor coordinates to the motor cortex;
2. A motor command $u$ is computed in the motor cortex and is transmitted to muscles via spinal motoneurons to generate a control torque $\tau$;
3. The musculoskeletal system realizes an actual movement $q$ by interacting with its environment;
4. The $q$ is measured by proprioceptors and is fed back to the motor cortex via the transcortical loop;
5. The spinocerebellum-magnocellular red nucleus system requires an internal neural model of the musculoskeletal system (i.e. internal forward model) while monitoring $u$ and $q$ to predict $q$, where the predictive error $\tilde{q}$ is transmitted to the motor cortex via the ascending pathway and to muscles through the rubrospinal tract as the modification of $u$;
6. The cerebrocerebellum-parvocellular red nucleus system requires an internal neural model for the inverse modeling of the musculoskeletal system (i.e. internal inverse model) while receiving the desired output $q_d$ and a feedback command $u_{FB}$;
7. As the motor learning proceeds, a feedback command $u_{FB}$ generated by the internal inverse model gradually takes place of $u_{FB}$ as the main command;
8. Once the internal inverse model is learnt, it generates the motor command $u$ directly using $q_d$ to perform various tasks precisely without external feedback.

The cerebellar neural circuit of a simplified FEL framework without the internal forward model is demonstrated in Fig. 1, in which the simple spikes of Purkinje cells represent sensory error signals in motor command coordinates.

3. PROBLEM FORMULATION

Consider a general class of robotic systems described by an Euler-Lagrange formulation (Pan et al., 2016a)¹:

$$M(q)\ddot{q} + C(q, \dot{q})q + G(q) + F(q) = \tau$$  

(1)

where $q(t) = [q_1(t), q_2(t), \ldots, q_n(t)]^T \in \mathbb{R}^n$ is a joint angle vector, $M(q) \in \mathbb{R}^{n \times n}$ is an inertia matrix, $C(q, \dot{q}) \in \mathbb{R}^{n \times n}$ is a centripetal-Coriolis matrix, $G(q) \in \mathbb{R}^n$, $F(q) \in \mathbb{R}^n$ and $\tau \in \mathbb{R}^n$ denote gravitational, friction, and control torque vectors, respectively, and $n$ is the number of links. It is assumed that $F(q)$ can be expressed as follows:

$$F(q) = F_c(q) + F_s \text{sgn}(q)$$  

(2)

with $F_c := \text{diag}(k_{c1}, k_{c2}, \ldots, k_{cn})$, $F_s := \text{diag}(k_{s1}, k_{s2}, \ldots, k_{sn})$, and $\text{sgn}(q) := [\text{sgn}(q_1), \text{sgn}(q_2), \ldots, \text{sgn}(q_n)]^T$, where $k_{ci} \in \mathbb{R}^+$ are coefficients of viscous friction, $k_{si} \in \mathbb{R}^+$ are coefficients of Coulomb friction, and $i = 1$ to $n$. For facilitating presentation, define a lumped uncertainty

$$H(q, \dot{q}, v, \dot{v}) := M(q)\dot{q} + C(q, \dot{q})v + G(q)$$  

(3)

with $v \in \mathbb{R}^n$ an auxiliary variable. The following properties from Pan et al. (2018) and definitions from Kingravi et al. (2012) are introduced to facilitate control design.

**Property 1:** $M(q)$ is a symmetric and positive-definite matrix which satisfies $m_0\|\zeta\|^2 \leq \zeta^TM(q)\zeta \leq m\|\zeta\|^2$, $\forall \zeta \in \mathbb{R}^n$, in which $m_0, m \in \mathbb{R}^+$ are some constants.

¹ It can be regarded as a simplified model of the musculoskeletal system where the muscle dynamics is ignored resulting in $\tau = u$.
Property 2: \( M(q) - 2C(q, \dot{q}) \) is skew-symmetric such that 
\[
\zeta^T(M(q) - 2C(q, \dot{q})) \zeta = 0, \quad \forall \zeta \in \mathbb{R}^n,
\]
implying the internal forces of the robot do not work.

Property 3: \( F(q) \) can be parameterized by
\[
F(q) = \Phi_T(q) W_T = \Phi_T(q) W_c + \Phi_T(q) W_e
\]
where \( \Phi_T := [\Phi_T^T(\dot{q}) | \Phi_T^T(\dot{q}) W_T] \) is a known regressor, \( W_T := [W_T, W_T]^T \in \mathcal{B}_{c_T} \subset \mathbb{R}^{2n} \) is an unknown parameter vector, \( c_T \in \mathbb{R}^+ \) is a certain constant, and
\[
\Phi_T := [\Phi_T(q_1, \dot{q}_1, \ldots, \Phi_T(q_n, \dot{q}_n)],\]
where \( \Phi_T(q) := \text{diag}(\text{sgn}(\dot{q}_1), \text{sgn}(\dot{q}_2), \ldots, \text{sgn}(\dot{q}_n)) \).

Property 4: \( H(q, \dot{q}, v, t) \) can be parameterized by
\[
H(q, \dot{q}, v, t) = \Phi_T(q, \dot{q}, v, t) W_h
\]
where \( \Phi_T : \mathbb{R}^{4n} \rightarrow \mathbb{R}^{N \times n} \) is a known \( \mathcal{C}_1 \) regressor, \( W_h \in \mathcal{B}_{h} \subset \mathbb{R}^{N} \) is an unknown parameter vector, \( c_h \in \mathbb{R}^+ \) is a certain constant, and \( N \) is the dimension of \( h \).

Definition 1: A bounded signal \( \Phi(t) \in \mathbb{R}^{N \times n} \) is of \( \mathcal{E} \) if \( \exists T_c, \tau_d, \sigma_e \in \mathbb{R}^+ \) such that
\[
\int_{t_0 - \tau_d}^{t} \Phi(t) \Phi(T) dt \geq \sigma_e I.
\]
Let \( c_w := (\alpha_1^2 + \alpha_2^2)^{1/2} \). It follows from (3)-(5) that the left side (1) can be written as a parameterized form:
\[
H(q, \dot{q}, v, t) + F(q, \dot{q}) = \Phi_T(q, \dot{q}, v, \dot{t}) W_h
\]
where \( \Phi_T(q, \dot{q}, v, \dot{t}) := \Phi_T(q, \dot{q}, v, \dot{t}) \Phi_T(q, \dot{q}) \Phi_T(q, \dot{q}) W_h \in \mathbb{R}^{N \times n} \) and \( W_h := [W_h, W_h]^T \in \mathcal{B}_{c_w} \subset \mathbb{R}^{N \times n} \).

Let \( \tilde{W}_h(t) \in \mathbb{R}^N, \tilde{W}_f(t) \in \mathbb{R}^{2n}, \tilde{W}_e(t) \in \mathbb{R}^n \) and \( \tilde{W}_c(t) \in \mathbb{R}^n \) denote estimates of \( W_h, W_f, W_e, \) and \( W_c \), respectively. Define a parameter estimation error \( \dot{W} := \dot{W} - \tilde{W} = [\tilde{W}_h^T, \tilde{W}_f^T, \tilde{W}_c^T]^T \), where \( \tilde{W} := [W_h^T, W_f^T, W_c^T]^T \in \mathbb{R}^{N+2n} \). Subtracting (13) results in
\[
\tilde{W}_h(t)W_h - \tilde{W}_f(t)W_f - \tilde{W}_c(t)W_c - \tilde{W}_e(t)W_e.
\]

In this subsection, we have \( v = \dot{q} \) in (5). Applying (6) to (1), one gets a parameterized robot model
\[
\tau(t) = \Phi_T(q(t), \dot{q}(t), \dot{q}(t)) W_h
\]
To eliminate the necessity of \( \dot{q} \) in parameter estimation, a linear filter \( \frac{\dot{q}}{s+\alpha} \) is applied to each side of (13) resulting in
\[
\tau_F(t) := \Phi_T(q(t), \dot{q}(t)) \dot{W}_h
\]
where \( s \) denotes a complex variable, \( \alpha \in \mathbb{R}^+ \) is a filtering parameter, \( \Phi_F := \alpha e^{-st} * \Phi \) and \( \tau_F := \alpha e^{-st} * \tau \) are filtered counterparts of \( \Phi \) and \( \tau \), respectively, and \( * \) is the convolution operator. A predictive model is given by
\[
\tau_F(t) = \Phi_T(q(t), \dot{q}(t)) \dot{W}(t)
\]
in which \( \tau_F \in \mathbb{R}^n \) is a predicted counterpart of \( \tau_F \). To facilitate presentation, define an excitation matrix
\[
\Theta(t) := \int_{t-\tau_d}^{t} \Phi_T(q(\tau), \dot{q}(\tau), \dot{q}(\tau)) \Phi_T(q(\tau), \dot{q}(\tau)) d\tau.
\]
The overall closed-loop system that combines the tracking with bounded parameter estimation under perturbations if with \( \Phi(\cdot) \in C^0 \) is obtainable by (17). A CEL law with switch-modification is used to guarantee closed-loop stability to 0 due to the page limitation. The LaSalle-Yoshizawa corollaries for nonsmooth systems are of use to measure the angle of each motor. Therefore, the resolutions of the three joints are 3.0 \times 10^{-2} \text{rad}, 4.0 \times 10^{-2} \text{rad}, and 4.8 \times 10^{-2} \text{rad}, respectively. The sampling time of the real-time control module is 1 ms.

The robot regression model in Xin et al. (2007) is introduced for implementation. The proposed CEL control law comprised of (11) and (19) is rewritten as follows:

\[
\begin{align*}
\dot{x}_i &= e_2 - \Lambda_1 e_1 \\
\dot{e}_2 &= M^{-1}(q) \left( \ddot{q} - C(q, \dot{q}) e_2 - K_c e_1 \right) \\
\dot{W} &= -\gamma (\Phi(x, q_\tau)) \dot{e}_2 + \kappa \xi - \sigma W.
\end{align*}
\]

A block diagram of the CEL robot control scheme is given in Fig. (2). If there exists \( T_e, \sigma_e, \tau_d \in \mathbb{R}^+ \) such that the IE condition \( \Theta(T_e) \geq \sigma I \) holds, the control parameters \( \Lambda_1, \Lambda_2, \gamma, \sigma_0 \) can be properly selected so that the closed-loop system has semiglobal stability in the sense that all signals are of \( L_{\infty} \) and \( e(t) \) asymptotically converges to 0 on \( t \in [0, \infty) \), and both \( e(t) \) and \( W(t) \) exponentially converge to 0 on \( t \in [T_e, \infty) \). The above results can be proven based on the Filippov’s theory of differential inclusions and the Lasalle-Yoshizawa corollaries for nonsmooth systems (Fischer et al., 2013), where the details are omitted here due to the page limitation.

![Fig. 2. A block diagram of the CEL robot control scheme.](Image 44x636 to 289x769)

The proposed CEL controller is implemented on a DENSO robot arm with a Quanser real-time control module [see Fig. 3]. Each joint of the robot arm is driven by an AC servo motor with a speed reducer, where the gear ratios of the three joints used in the experiments are 160, 120, and 100, respectively. A 17-bit absolute rotary encoder is used to measure the angle of each motor. Therefore, the resolutions of the three joints are 3.0 \times 10^{-2} \text{rad}, 4.0 \times 10^{-2} \text{rad}, and 4.8 \times 10^{-2} \text{rad}, respectively. The sampling time of the real-time control module is 1 ms.

![Fig. 3. Experimental setup: A 6-axis articulated robot. (a) A Denso robot arm (Type: VP6242G). (b) A Quanser open architecture real-time control module.](Image 436x642 to 545x770)

5. INDUSTRIAL ROBOT APPLICATION

The proposed CEL controller is implemented on a DENSO robot arm with a Quanser real-time control module [see Fig. 3]. Each joint of the robot arm is driven by an AC servo motor with a speed reducer, where the gear ratios of the three joints used in the experiments are 160, 120, and 100, respectively. A 17-bit absolute rotary encoder is used to measure the angle of each motor. Therefore, the resolutions of the three joints are 3.0 \times 10^{-2} \text{rad}, 4.0 \times 10^{-2} \text{rad}, and 4.8 \times 10^{-2} \text{rad}, respectively. The sampling time of the real-time control module is 1 ms.

The robot regression model in Xin et al. (2007) is introduced for implementation. The proposed CEL control law comprised of (11) and (19) is rewritten as follows:

\[
\begin{align*}
\dot{\tau} &= K_c e + \Phi(T, q_\tau) \dot{W} \\
\dot{W} &= \gamma (\Phi(x, q_\tau)) e_2 + \kappa \xi - \sigma W.
\end{align*}
\]

where the values of the control parameters are selected as \( \Lambda_1 = \text{diag}(4, 4, 8) \) and \( \Lambda_2 = \text{diag}(6, 6, 1.5) \) in (11), \( \alpha = 5 \) in (14), \( \tau_d = 4 \) in (16), and \( \gamma = 0.15 \). The baseline controller is chosen as the classical FEL control law as follows:

\[
\begin{align*}
\dot{\tau} &= K_c e + \Phi(T, q_\tau) \dot{W} \\
\dot{W} &= \gamma (\Phi(x, q_\tau)) e_2 - \sigma W,
\end{align*}
\]

where the control parameters are selected to be the same values as the proposed control law for fair comparison.

To verify the learning ability of the proposed controller, the desired joint position \( q_d \) is expected to be simple. Consider a regulation problem with \( q_d \) being generated by

\[
\begin{align*}
\bar{q}_{d1} &= 0 \\
\bar{q}_{d2} &= 0 \\
\bar{q}_{d3} &= 0 \\
\bar{q}_{d4} &= 0,
\end{align*}
\]

with \( i = 1 \) to 3 and \( q_{d4}(0) = 0 \), where \( q_{c1}(t) \) is a step trajectory that repeats every 50 s. The experiments last for 250s, and thus, there are five control tasks. The units of joint position and torque are rad and N.m, respectively. Let \( e_{11} = [e_{111}, e_{112}, e_{123}]^T \), where \( e_{11i} \in \mathbb{R} \) denotes the position tracking error for Joint \( i \) with \( i = 1 \) to 3.

Table I provides control results of the two controllers for both the first (before learning) and the last tasks (after learning). For the classical FEL control, there exists a large tracking deviation between the desired position \( q_d \) and the actual position \( q \) for the first task. The learning for
200 s, the tracking performance is slightly improved for the last task. As an example, the range of the tracking error $e_{11}$ after learning for Joint 1 is reduced from $[-1.206, 2.016]$ (before learning) to $[-0.679, 1.044]$ ($\approx 52\%$ of that before learning) under the classical FEL control.

For the proposed CEL control, a large tracking error $e_1$ still exists before learning. During the first task, the IE condition is met. After the learning for 200 s, the proposed CEL control improves significantly in tracking accuracy compared with that before learning. For example, the range of $e_{11}$ after learning for Joint 1 is reduced from $[-0.921, 0.912]$ (before learning) to $[-0.284, 0.152]$ (only $\approx 24\%$ of that before learning) under the proposed FEL control. The strong learning capacity of the proposed CEL control is also clearly shown by comparing the ranges of $e_1$ under the two controllers in Table 1.

It is also demonstrated in Table 1 that the maximal control torques $\tau$ of the proposed CEL control are much smaller than those of the classical FEL control for all joints and tasks, which implies that the proposed CEL control is able to achieve much better tracking accuracy even using much smaller control gains and much less energy cost. This is because the improved feedforward control resulting from accurate parameter estimation is beneficial for reducing feedback control torques. The control torque $\tau$ of joint 3 shows slight oscillations compared with those of joints 1 and 2 due to its more significant joint elasticity caused by the unique synchronous belt drive mechanism. This is also the reason why the performance improvement of joint 3 by the proposed CEL control shown in Table 1 is not as significant as those of joints 1 and 2.

Fig. 4 provides performance comparisons of the two controllers. For the classical FEL control, as the PE condition does not hold for the entire control process, no parameter convergence is shown [see Fig. 4(b)]. In sharp contrast, the proposed CEL control achieves fast convergence of $\|\hat{W}\|$ to a certain constant [see Fig. 4(b)]. This is consistent with the theoretical analysis: The proposed CEL control only requires the much weaker IE condition for parameter convergence, which can be satisfied during the transient process of the first task. Also, the CEL control achieves a smaller $\|\hat{e}_1\|$ than the FEL control even from the first control task owing to the predictive error feedback in the CEL law, and maintains the superior tracking performance during the entire control process [see Fig. 4(a)].

6. CONCLUSIONS

In this paper, a novel CEL framework has been developed for robot control under discontinuous friction. Compared with the classical FEL control, the distinctive features of the proposed approach include: 1) Semiglobal stability of the closed-loop system is ensured without high feedback gains; 2) exact robot modeling is ensured by the weakened IE condition. The proposed approach has been applied to a DENSO industrial robot, and experimental results have shown that it is superior with respect to tracking accuracy and control energy compared with the classical FEL control. Future work would focus on the optimization of the experimental setup to speed up parameter convergence and the applications of the proposed approach to more real-world robotic systems (Liu et al., 2021a,b).

Table 1. A comparison of performance indices for the two controllers

| Ranges of $e_1$ and $\tau$ | The classical FEL Control | The proposed CEL control |
|----------------------------|----------------------------|--------------------------|
| Joint 1 | Joint 2 | Joint 3 | Joint 1 | Joint 2 | Joint 3 |
| $e_1$ before learning ($^\circ$) | $[-1.206, 2.016]$ | $[-1.175, 1.976]$ | $[-3.876, 2.297]$ | $[-0.921, 0.912]$ | $[-1.590, 1.911]$ | $[-2.973, 0.908]$ |
| $e_1$ after learning ($^\circ$) | $[-0.679, 1.044]$ | $[-1.519, 0.969]$ | $[-3.136, 1.509]$ | $[-0.284, 0.152]$ | $[-0.415, 0.098]$ | $[-1.708, 1.406]$ |
| $\tau$ before learning (N.m) | $[-5.478, 11.08]$ | $[-11.21, 6.738]$ | $[-10.51, 8.289]$ | $[-1.307, 7.059]$ | $[-6.246, 3.358]$ | $[-7.832, 5.458]$ |
| $\tau$ after learning (N.m) | $[-5.105, 7.909]$ | $[-9.304, 8.865]$ | $[-10.90, 6.932]$ | $[-1.837, 6.604]$ | $[-7.927, 3.721]$ | $[-7.861, 5.774]$ |

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