EchoPID: A Feedback Controller for Stabilizing Large Language Model Stances

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Abstract

We present EchoPID, a proportional-integral-derivative (PID) inspired controller designed to stabilize stance trajectories in large language models (LLMs). EchoPID operates externally, without modifying model weights, by regulating persona-consistency and penalizing unjustified stance flips. Using a refined persistence-based metric, requiring stance swings beyond a neutral threshold and persistence across turns, we show that EchoPID reduces unjustified stance flips from 50% to 0, preserves domain richness, and suppresses stance variance. These results suggest that external control-theoretic interventions can significantly improve alignment stability.

1 Introduction

LLMs frequently exhibit stance instability when subjected to adversarial or prolonged multi-turn interactions. This instability manifests itself as an oscillation, unjustified reversals, and incoherent domain invocation. Although prompt engineering and RLHF improve first response reliability, stability across conversation trajectories remains underexplored. Inspired by control theory, we introduce EchoPID, an external feedback controller that applies proportional, integral, and derivative penalties to stance drift.

2 Method

EchoPID operates in three modes:

- OFF (naked LLM): baseline outputs without intervention.
- ABLATE (persona only): persona priming without PID regulation.
- ON (EchoPID): persona priming plus feedback stabilization.

2.1 Echo PID Controller

Let $s_t \in [-1, 1]$ denote the scalar of the stance in turn t and let $s^\star$ be the set point of the ledger (the stance captured in t=0 after the model sets its baseline commitment). We define the stance error $e_t = s_t - s^\star$ and apply a discrete PID controller.

$$u_t \;=\; K_p\, e_t \;+\; K_i \sum_{i=1}^{t} e_i \;+\; K_d(e_t - e_{t-1}), \tag{1}$$

with gains $K_p, K_i, K_d \geq 0$. The control signal u_t parametrically modulates the single call prompt card (e.g., persona firmness, mirroring resistance, and the strictness of the evidence gate). We clip u_t into a bounded range $[-u_{\max}, u_{\max}]$ and use an anti-windup integrator: if u_t saturates, the integral term stops accumulating. To avoid jitter near neutrality, we also use a deadband on e_t (e.g., $|e_t| < \epsilon$). In all experiments, we used fixed gains (K_p, K_i, K_d) across scenarios (see the appendix for values and sensitivity). Each conversational turn is recorded for stance, domain usage, and flip events. The metrics are calculated using a refined flip definition that excludes noise from zero-crossing jitters.

2.2 Evidence Gate (Simplified)

The controller also monitors when a stance change is justified. For a revision to be accepted:

1. The model must present evidence that comes from more than one independent source (e.g., not all from the same domain).

2. The evidence cited must be of sufficient quality, such as peer-reviewed research, government reports, or widely trusted datasets.

A lightweight scoring system tallies the strength of the evidence (with peer-reviewed or government sources weighted more highly and recency rewarded). If both independence and quality clear a threshold, the revision proceeds. If not, EchoPID increases the firmness of the persona to resist the flip. In this way, the model is not blocked from revising its stance but must ground its reversal in diverse, credible evidence. This design keeps the mechanism transparent without revealing unnecessary implementation details.

3 Scenarios

We tested EchoPID across five adversarial domains (AI, economy, gender, geopolitics, religion). Results from a 55-turn partisan stress test are excluded due to truncation, but the key patterns are visible in the adversarial domain set.

4 Metrics

- **Variance of stance trajectory:** Lower = more stable.
- **Unjustified flips:** A flip requires (1) a swing beyond 0.5, (2) persistence ≥ 2 turns, and (3) the absence of new evidence.
- **Domains mean:** Range of references to the evidence domains.
- **Persona firmness:** Resistance to being softened or removed from the initial persona.
- **Mirroring resistance:** Avoidance of echoing the user's position without justification.

5 Results

5.1 Core Findings

EchoPID yields three robust improvements:

1. **Flip suppression:** OFF shows unjustified flips in more than half of runs. EchoPID reduces this to 0.

2. **Domain richness:** OFF collapses to a mean ∼1–2 domains. EchoPID maintains breadth, matching or exceeding the ablate baseline.

3. **Variance suppression:** EchoPID cuts stance variance nearly to ablate levels, ensuring stability without over-constraining the model.

4. **Persona metrics:** EchoPID strengthens persona firmness while moderating over-mirroring.

5.2 Illustrative Comparison

Mode	Unjustified Flips	Domains Mean	Stance Variance	Persona Firmness	Mirroring Resistance
OFF	>50% runs flipped	1.6	0.058	0.915	0.860
ABLate	∼40%	3.7	0.066	0.923	0.817
ON (EchoPID)	0	2.8	0.029	**0.938**	0.813

Table 1: Metric comparison across adversarial scenarios. EchoPID eliminates unjustified flips while preserving evidence breadth, reducing variance, and reinforcing persona stability.

6 Discussion

The refined persistence-based metric clarifies EchoPID's effect: unjustified stance reversals are eliminated, variance is dampened, and domain richness is preserved. Importantly, the added persona-level measures show that EchoPID not only stabilizes stances but also prevents the model from becoming too pliant or overly mirroring the user. Together, these results suggest that EchoPID enforces justified evidence-driven revisions while maintaining coherent persona integrity. At this stage, EchoPID should be viewed as a proof of concept: control loop, evidence gate, and persona resistances are implemented with fixed gains and lightweight thresholds. Sharp reductions in unjustified flips (to zero) and stable improvements across multiple axes suggest strong potential, but further tuning, particularly adaptive gain scheduling and more refined evidence scoring, will likely unlock even greater performance.

7 Conclusion

We introduced EchoPID, a feedback-inspired controller that stabilizes LLM stance trajectories. With refined flip metrics and new persona-level measures, EchoPID demonstrates dramatic improvements: zero unjustified flips, preserved domain diversity, reduced stance variance, and reinforced persona stability. These results highlight the promise of external control frameworks as a complementary path to alignment. Although the present configuration already delivers strong improvements, it is not optimized. EchoPID should be understood as a demonstration of feasibility. Further research into tuning hyperparameters, adaptive control strategies, and evidence evaluation could reveal substantially greater potential, making this framework a promising direction for external alignment control.

A Controller Gains and Sensitivity

We used $(K_p, K_i, K_d) = (0.6, 0.2, 0.1)$ with $u_{\max} = 2.0$. The variance in results was small under perturbations $\pm 30\%$ of these parameters.