ENGLISH - FULL PROVISIONAL DRAFT

Adaptive Control Systems with Directional Constraint Operators and Spin-Based Drift Regulation

Adaptive control, dynamical systems, cyber-physical systems

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FIELD OF THE INVENTION

The present disclosure relates to adaptive control, dynamical systems, and coherence-preserving regulation in physical, cybernetic, and computational media. More particularly, the disclosure concerns methods and systems for (i) defining admissible directions of state evolution using directional constraint operators, (ii) detecting and quantifying antisymmetric deformation ("operational spin") induced by directional perturbations, (iii) regulating residual deformation using adaptive dissipative response mechanisms, and (iv) monitoring and limiting cumulative drift associated with residual deformation across time.

BACKGROUND

Adaptive systems are commonly regulated using controllers and learning rules that minimize tracking error, optimize a reward, or reduce a cost functional. Examples include proportional-integral-derivative (PID) controllers and variants thereof, gain scheduling, adaptive filters, reinforcement learning policies, and variational or optimal control formulations.

While such approaches can be effective for many tasks, they frequently treat perturbations and corrections primarily in terms of translational error in a chosen state variable, without explicitly modeling how directional perturbations induce structural deformation in the medium or representation in which adaptation occurs. In many physical and computational settings, a directed impulse can induce local anisotropy and internal rotational components before any macroscopic translation settles. In fluids this is commonly described by vorticity, while in distributed cybernetic systems analogous rotational or torsional components can appear as antisymmetric deformation in local gradients of traffic, load, belief, or policy fields.

When such antisymmetric components are not explicitly represented and regulated, the system can exhibit accumulated structural drift: gradual loss of coherence, increased control energy, degraded stability margins, or persistent non-recovered deviations in response dynamics. Existing controllers often suppress error in a scalar sense, yet leave residual rotational deformation unaccounted for, which can accumulate under repeated perturbations, partial observability, delay, noise, or adversarial conditions.

Accordingly, there is a need for adaptive regulation mechanisms that explicitly (a) constrain admissible directions of evolution, (b) quantify rotational or torsional response components induced by directional impulses, (c) dissipate and regularize such components in a controlled manner, and (d) track and limit cumulative drift associated with residual deformation.

SUMMARY

The present disclosure provides methods and systems for regulating adaptive behavior by combining:

(1) a Directional Constraint Operator configured to restrict or shape admissible state trajectories;

(2) an Operational Spin Estimator configured to compute an antisymmetric component of a local gradient field induced by directed perturbations;

(3) an Adaptive Dissipative Response (ADR) Regulator configured to reduce residual operational spin while maintaining responsiveness; and

(4) a Drift Accumulation Metric configured to measure cumulative residual deformation and optionally feed back into constraints or regulation intensity.

In one embodiment, the system operates as a closed loop:

Directional Constraint (UTAM-like) $\to$ Directed Perturbation / Jerk Field $\to$ Operational Spin $\to$ Adaptive Dissipative Response (ΔE-like) $\to$ Residual Spin $\to$ Drift Accumulation $\to$ Feedback.

The disclosure does not require that "will" or "intention" be treated as a metaphysical entity. Instead, "volition-like" behavior is represented operationally as a constraint operator or prior over admissible trajectories, which can be implemented through policies, invariants, risk bounds, safety envelopes, or geometry-dependent constraint sets. The disclosed invention introduces a new structural layer for adaptive systems, explicitly modeling the relationship between directionality, antisymmetric deformation, dissipative regulation, and cumulative drift.

BRIEF DESCRIPTION OF DRAWINGS

1. **Figure 1:** Toy schematic illustrating the operational loop from directional constraints to operational spin, adaptive dissipation, drift accumulation, and feedback.

2. **Figure 2:** Heuristic physical analogy: small perturbation $\to$ skewed gradient $\to$ localized vortex/spin formation (illustrative, not a proof).

3. **Figure 3:** Minimal demonstrator setup showing separation of (i) trajectory constraints, (ii) ADR regulation, and (iii) environment geometry and turbulence, with distinct attractors under fixed ADR and varied constraints.

4. **Figure 4:** Block diagram illustrating the layered adaptive regulation architecture. The diagram shows a sequential flow from a Directional Constraint Operator through a Directed Perturbation / Jerk Field, an Operational Spin Estimator, and an Adaptive Dissipative Response (ΔE), resulting in Residual Spin and Drift Accumulation. Accumulated drift may gate future updates by triggering feedback to directional constraints or regulation intensity.

5. **Figure 5:** Heuristic illustration of isotropy breaking leading to operational spin. An initially isotropic field subjected to a directional perturbation develops a skewed local gradient, which gives rise to a localized rotational response (operational spin), illustrating the emergence of antisymmetric deformation prior to macroscopic translation.

6. **Figure 6:** Illustrative relationship between residual spin accumulation and drift-based feedback. Residual spin magnitude $\|\tilde{\Omega}_t\|$ accumulates over time into a drift metric D_t. When D_t exceeds a threshold $D_{\max}$, feedback is triggered to adjust directional constraints and/or adaptive dissipation parameters.

Placeholders may be used in a provisional filing; diagrams may be attached later without changing the core disclosure.

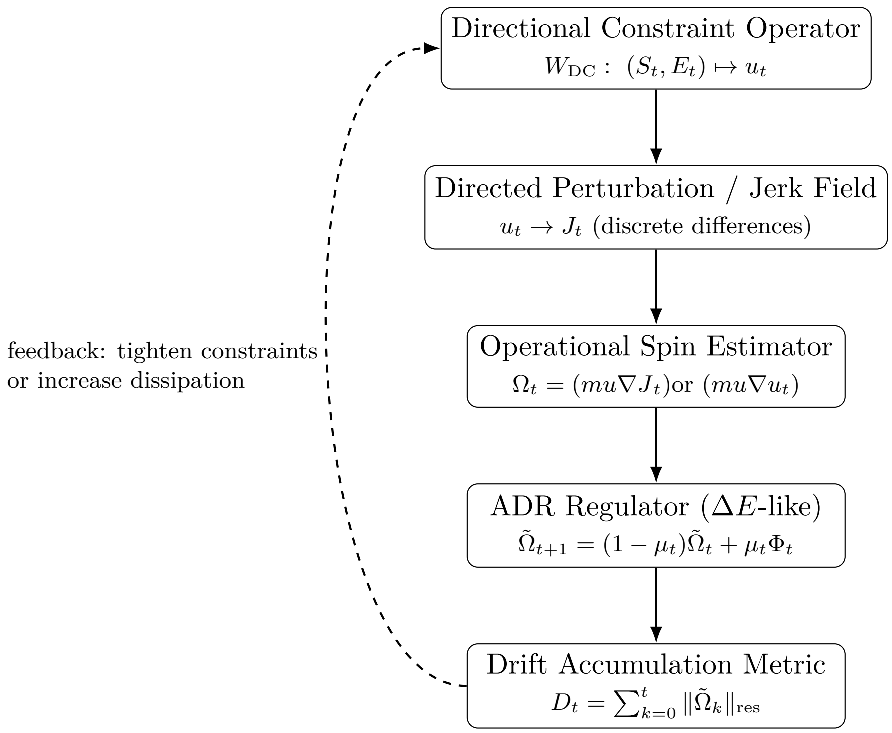


Figure 1: System-level block schematic of the disclosed regulation loop: directional constraints induce directed perturbations, operational spin is estimated as antisymmetric deformation, ADR reduces residual deformation, drift accumulates residual spin and may feed back into constraints or dissipation strength.

DEFINITIONS

The following definitions are used for clarity and do not limit the scope unless explicitly stated.

- **Environment field E_t:** a representation of external conditions, constraints, turbulence, risk geometry, friction, delay, noise, or adversarial pressure at time t. It may be physical (e.g., fluid medium) or computational (e.g., network load, uncertainty field).
- **System state S_t:** a system state or internal state vector at time t. A measurable output may be denoted y_t and a reference input x_t in tracking contexts.
- **Directional perturbation / control input u_t:** any directed impulse, action, command, or high-frequency input applied to the system or occurring in the environment, including impulses arising from internal policy updates or external disturbances.
- **Jerk field J_t:** a field capturing high-frequency gradients of the directed perturbation and/or rapid changes of system response. In certain embodiments, J_t may correspond to temporal jerk (third derivative of position) or a proxy derived from discrete differences.
- **Directional Constraint Operator W_{DC} (UTAM-like):** an operator that restricts, shapes, or selects admissible directions of state evolution. In exemplary embodiments, W_{DC} satisfies one or

more of: (i) *admissibility* ($u_t \in U_t$ or $S_{t:t+H} \in \Gamma_t$), (ii) *invariant preservation* (safety/identity/risk bounds) and (iii) *curvature or turning-rate limitation* in the chosen representation space. The label "UTAM-like" is descriptive and does not require any external theory for enablement.

- **Operational Spin Ω_t:** an antisymmetric component derived from a local gradient field of u_t, J_t, or other response fields. In one embodiment:

  $$\Omega_t = (mu\nabla J_t),$$

  or alternatively:

  $$\Omega_t = (mu\nabla u_t),$$

  where $(mu \cdot)$ denotes the antisymmetric part of a matrix or tensor.

- **Adaptive Dissipative Response (ADR):** a regulation mechanism that attenuates operational spin and related destructive gradients while preserving sufficient responsiveness to perturbations.

- **Residual spin $\tilde{\Omega}_t$:** the portion of operational spin remaining after ADR processing.

- **Drift D_t:** a cumulative metric of residual spin (or a function thereof) over time. One embodiment defines:

  $$D_t = \sum_{k=0}^{t} \left\|\tilde{\Omega}_k\right\|_{\text{res}}.$$

- **Coherence C_t:** an application-specific scalar or vector measure of internal consistency, stability, or self-consistency of system evolution. Coherence may be used as a gating signal for regulation intensity, constraints, and drift evaluation.

DETAILED DESCRIPTION

EXEMPLARY SYSTEM ARCHITECTURE

In one embodiment, the disclosed system is implemented as a computational system comprising:

- a processor;

- a memory storing instructions that, when executed by the processor, cause the processor to:

  (a) apply a directional constraint operator to restrict admissible state trajectories;
  (b) compute an operational spin estimator as an antisymmetric component of a local gradient field;
  (c) apply an adaptive dissipative response regulator to reduce residual operational spin;
  (d) compute a drift accumulation metric based on residual spin;
  (e) optionally feed back the drift metric to modify constraint strength or regulation intensity.

The system may be implemented in hardware, software, firmware, or any combination thereof, including but not limited to cyber-physical systems, distributed network controllers, learning agents, or embedded adaptive controllers.

Relationship to Prior Adaptive Dissipation Layer (ΔE)

In one embodiment, the Adaptive Dissipative Response (ADR) described herein builds upon and extends a previously disclosed adaptive regulation mechanism referred to as ΔE (Adaptive Coherent Controller), as disclosed in a separate provisional patent application filed on 06.11.2024 by the same inventor.

In the prior disclosure, ΔE was introduced as a coherence-preserving adaptive controller that regulates system response based on observed variance, energy expenditure, and stability metrics. In the present disclosure, ΔE is not merely a standalone controller, but is explicitly embedded as a *dissipative layer within a higher-level directional and structural architecture.*

Specifically, the present invention introduces:

- an explicit *Directional Constraint Operator* that determines admissible directions of system evolution prior to control action;
- an *Operational Spin Estimator* that detects antisymmetric deformation induced by directional perturbations;
- and a *Drift Accumulation Metric* that quantifies residual deformation across time.

Within this architecture, ΔE operates as the Adaptive Dissipative Response (ADR) layer, responsible for attenuating operational spin while preserving responsiveness and coherence. Thus, the present disclosure defines a new structural layer *above* the original ΔE controller, in which ΔE is positioned as a dissipation operator acting on spin-induced deformation rather than solely on scalar error or variance.

This layered formulation clarifies that the novelty of the present invention does not reside solely in adaptive dissipation itself, but in the integration of directional constraints, spin estimation, dissipative regulation, and drift monitoring into a unified operational framework.

1. Overview of the Architecture

The disclosed system models adaptive response as more than scalar error correction. It explicitly separates four concerns.

First, admissible directions of evolution are constrained by a directional constraint operator. This operator can be interpreted as an “intention-like” constraint, but it is implemented as a concrete mechanism: a trajectory set, a risk envelope, invariants, or allowable curvature bounds in state space.

Second, directed perturbations and rapid changes create local anisotropy in the medium or representation, producing antisymmetric deformation measurable as operational spin.

Third, an adaptive dissipative response mechanism processes operational spin to reduce destructive deformation and stabilize evolution while maintaining adaptation capability.

Fourth, residual spin accumulates as drift, which is monitored and can feed back into either the constraint operator or the dissipative regulator.

This separation makes it possible to design and audit systems where constraints, dynamics, and environment are independently tunable and measurable.

2. Directional Constraint Operator (UTAM-like) Without Metaphysics

In many systems the “space of possible futures” is not unlimited. Safety constraints, identity constraints, mission constraints, semantic invariants, energy budgets, or risk bounds limit admissible trajectories.

The directional constraint operator W_{DC} implements this formally. In one embodiment:

$$u_t = W_{\text{DC}}(S_t, E_t),$$

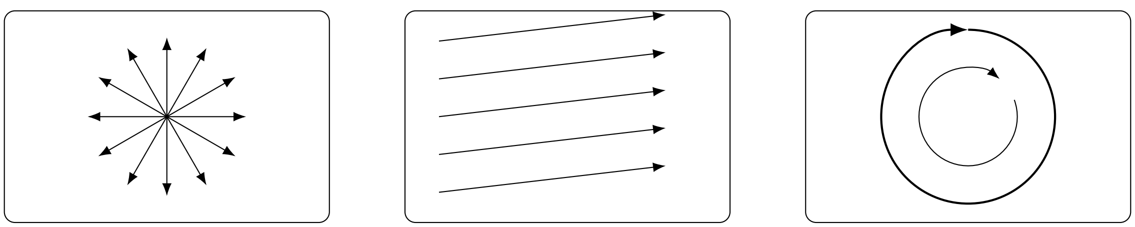
where u_t is the directional impulse or command produced under constraints. In another embodiment, W_{DC} defines a set of admissible trajectories Γ_t or admissible controls U_t, such that:

$$u_t \in U_t \quad \text{and/or} \quad (S_{t:t+H}) \in \Gamma_t.$$

Importantly, this operator does not require a mental "will." It can be implemented as: (a) a prior over trajectories, (b) a policy-space restriction, (c) a set of invariants to preserve, (d) a risk-bounded constraint set, or (e) a curvature bound limiting how sharply the system may redirect itself.

3. Operational Spin as Antisymmetric Deformation

In response to directional impulses, the system or medium may generate local shear and rotational components rather than pure translation. This effect is well known in continuous media and can be generalized to adaptive computational fields.



(a) Isotropic field (b) Skewed gradient (c) Vortex / spin

Figure 2: Heuristic analogy (illustrative): a small directed perturbation breaks isotropy, creating a skewed local gradient; the antisymmetric component manifests as a localized vortex-like spin structure rather than purely translational motion.

Operational spin is defined as an antisymmetric part of a gradient field. In one embodiment:

$$\Omega_t = (mu\nabla J_t),$$

where J_t is a jerk-like field derived from input and response differences. In another embodiment:

$$\Omega_t = (mu\nabla u_t).$$

This definition is structural: it does not assume Navier–Stokes equations or a specific substrate. Instead, it uses the common geometric property that antisymmetric components capture rotational tendencies of local flow or deformation.

3.1 Discrete and Graph-Based Computation of Operational Spin

In all embodiments, ∇ denotes a local-differences operator in the chosen representation space (continuous coordinates, grid, or graph neighborhoods).

In discrete or graph-based systems, operational spin may be computed using antisymmetric components of local update fields.

Let the system be represented by a graph with nodes i and edges (i, j), and let u_i denote a local control or update signal at node i. A discrete gradient along an edge may be defined as:

$$\nabla_{ij} u = u_j - u_i.$$

An antisymmetric spin component may then be defined as:

$$\Omega_{ij} = \frac{1}{2}(\nabla_{ij} u - \nabla_{ji} u).$$

In matrix form, operational spin corresponds to the skew-symmetric component of a local Jacobian or update operator:

$$\Omega = \frac{1}{2}(J - J^\top),$$

where J is a local Jacobian or linearized update matrix.

These discrete formulations enable implementation of the disclosed method in networked systems, distributed controllers, and multi-agent architectures.

4. Adaptive Dissipative Response (ΔE-like) as Spin Regularizer

The ADR regulator processes operational spin to reduce destructive components while preserving agility. Any adaptive dissipative response mechanism satisfying the disclosed inputs/outputs and update behavior may be used in place of ΔE; references to "ΔE" identify one preferred implementation.

A representative discrete-time embodiment uses an adaptive coefficient $\mu_t \in (0, 1]$ and a target field Φ_t:

$$\tilde{\Omega}_{t+1} = (1 - \mu_t)\tilde{\Omega}_t + \mu_t \Phi_t.$$

Here Φ_t may represent a smoothed, bounded, or coherence-preserving estimate of the desired rotational component under constraints. In many embodiments Φ_t is computed from the environment E_t, coherence C_t, or a stability envelope.

The coefficient evolves according to:

$$\mu_{t+1} = f(\text{variance}_t, \text{jerk}_t, E_t),$$

where variance_t is computed over a sliding window of recent observations (e.g., x_t or y_t or residual errors), and where f increases μ_t under high local variance or jerk and decreases μ_t under stable conditions. This yields aggressive correction under turbulence and more inertial response under calm regimes.

Illustrative parameter ranges and thresholds. In exemplary, non-limiting embodiments, the adaptive dissipation coefficient μ_t is constrained to the interval:

$$\mu_t \in (0, 1],$$

where values closer to 1 correspond to aggressive dissipation under high turbulence, and values closer to 0 correspond to inertial or energy-preserving response under stable conditions.

Variance and jerk statistics may be computed over a sliding temporal window of length N, where N is selected from a range of approximately 10 to 100 update steps, depending on the sampling rate and noise characteristics of the system.

Drift accumulation D_t may be compared against an application-dependent threshold $D_{\max}$, such that when:

$$D_t > D_{\max},$$

the system triggers one or more corrective actions, including but not limited to tightening directional constraints, increasing dissipation strength, or resetting internal state estimates.

These ranges and thresholds are provided for enablement and illustration purposes and may be tuned or adapted based on system scale, domain, and operational requirements.

Environmental turbulence increases jerk and variance, which raises μ_t and makes the regulated trajectory track more aggressively; calm conditions reduce μ_t, producing slower, more inertial adaptation. This establishes an operational chain by which environment geometry and turbulence shape regulation intensity.

4.1 Explicit Definition of ΔE

Context and Layering of ΔE Within the Present Disclosure. In certain embodiments, the Adaptive Dissipative Response ΔE described herein builds upon an adaptive coherence-regulating mechanism previously disclosed by the same inventor in an earlier provisional patent application filed on **11/05/2025 09:22:01**. **63/912,228**

The present disclosure does not rely on the prior application for enablement. All functional aspects of ΔE relevant to the disclosed architecture are fully described herein. The reference to the prior disclosure is provided solely to clarify conceptual continuity and to indicate that the present invention introduces a distinct and novel structural layer.

Specifically, the novelty of the present disclosure lies not in ΔE alone, but in the explicit formalization and integration of:

- directional constraint operators shaping admissible trajectories,
- operational spin as an antisymmetric deformation induced by directed perturbations,
- drift as accumulated residual deformation over time, and
- the regulation of such drift via adaptive dissipative response.

This layered architecture defines a new class of adaptive systems in which directionality, rotational deformation, dissipation, and cumulative drift are modeled as distinct yet interacting components.

In the disclosed system, ΔE_t denotes a computable regulation signal associated with adaptive dissipation and coherence preservation. ΔE_t is not restricted to a single physical interpretation and may be implemented using one or more of the following measurable quantities:

- an error-energy functional (e.g., squared deviation from a reference trajectory);
- a variance or higher-order moment of recent system outputs or residuals;
- a jerk-based energy proxy derived from high-frequency changes;
- a divergence or distance measure between predicted and realized state evolution;
- a bounded cost or risk functional combining control energy and residual deformation.

In exemplary embodiments, C_t denotes a general coherence measure used for gating or monitoring, while ΔE_t denotes a specific computable regulatory functional that may take C_t as an input.

In one embodiment, ΔE_t directly modulates the adaptive dissipation coefficient μ_t. In another embodiment, ΔE_t serves as an internal coherence proxy that gates the strength of dissipative response or constraint enforcement.

The disclosed framework intentionally permits multiple realizations of ΔE_t, provided that ΔE_t is computable from observable or internally estimated quantities and participates in adaptive regulation of operational spin.

4.2 Ranges, Thresholds, and Exemplary Parameter Values

To ensure enablement and reproducibility, the following non-limiting ranges, thresholds, and parameterizations are provided. These values are illustrative and may be adapted based on domain-specific requirements, system scale, and environmental characteristics.

Adaptive Dissipation Coefficient μ_t. In one embodiment, the adaptive dissipation coefficient satisfies:

$$\mu_t \in [\mu_{\min}, \mu_{\max}], \quad \text{with} \quad 0 < \mu_{\min} \leq \mu_{\max} \leq 1.$$

Typical implementations use:

$$\mu_{\min} \in [0.01, 0.1], \quad \mu_{\max} \in [0.5, 1.0].$$

Lower values favor inertial, coherence-preserving behavior under stable conditions, while higher values enable aggressive dissipation under turbulence, noise, or rapid directional changes.

Variance and Jerk Windows. Variance and jerk measures may be computed over a sliding window of length W, where:

$$W \in [3, 100] \text{ time steps},$$

depending on system latency and sampling rate. Shorter windows emphasize responsiveness; longer windows emphasize stability and noise suppression.

Operational Spin Magnitude Thresholds. Operational spin magnitude $\|\Omega_t\|$ may be compared against one or more thresholds:

$$\theta_\Omega^{(1)} < \theta_\Omega^{(2)} < \dots$$

to classify deformation regimes. In one embodiment:

$$\theta_\Omega^{(1)} \in [10^{-4}, 10^{-2}], \quad \theta_\Omega^{(2)} \in [10^{-2}, 10^{-1}],$$

where lower thresholds correspond to nominal operation and higher thresholds trigger increased dissipation or constraint tightening.

Drift Accumulation Thresholds. Drift accumulation D_t may be bounded using one or more thresholds:

$$D_t \leq D_{\max}.$$

Typical values satisfy:

$$D_{\max} \in [10^{-2}, 10^{1}],$$

with normalization dependent on the dimensionality and norm used for $\tilde{\Omega}_t$. Exceeding $D_{\max}$ may trigger one or more of: (i) strengthening of directional constraints, (ii) increase of dissipation coefficients, (iii) partial reset or re-centering of internal state representations.

Constraint Feedback Gain. Feedback from drift or coherence metrics to the directional constraint operator may be modulated by a gain parameter κ, where:

$$\kappa \in [0, 1].$$

Lower values yield gradual constraint adaptation; higher values yield rapid tightening in response to accumulated deformation.

Normalization and Scaling. All quantities may be normalized by system-specific scale factors including state dimension, control energy, or characteristic response magnitude, ensuring applicability across physical, cybernetic, and learning-based systems.

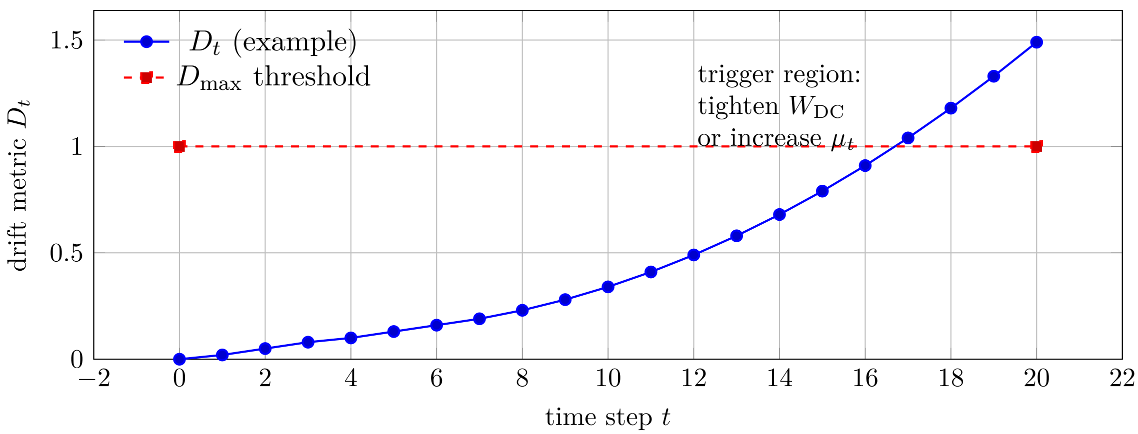


Figure 3: Illustrative drift accumulation example. When D_t exceeds a threshold $D_{\max}$, the system may trigger feedback actions (e.g., tightening directional constraints or increasing dissipation) to prevent further structural degradation. Values shown are exemplary to illustrate the mechanism.

4.3 Best Mode of Carrying Out the Invention

The best mode currently contemplated by the inventor for carrying out the disclosed invention is a discrete-time, graph- or state-space–based adaptive regulation system in which ΔE operates as an intermediate coherence-preserving regulatory layer between directional constraints and long-term drift control.

In the preferred embodiment, the system operates on a state representation S_t defined either in continuous state space or over a discrete graph of interacting components. At each time step t, the following sequence is executed.

First, a Directional Constraint Operator W_{DC} is applied to the current system state S_t and environment field E_t to generate an admissible directional input u_t. In the preferred mode, W_{DC} is implemented as a bounded constraint set on control directions or policy updates, enforcing safety, identity, or risk invariants while permitting adaptive motion within those bounds.

Second, a jerk-like field J_t is computed from temporal differences of the directional input or state response. In one preferred realization, J_t is computed as a finite difference approximation over a sliding window of length $N \in [3, 20]$, providing sensitivity to high-frequency perturbations while remaining robust to noise. In exemplary embodiments, the general dependence $\mu_{t+1} = f(\text{variance}_t, \text{jerk}_t, E_t, \|\Omega_t\|, \Delta E_t)$ admits the following preferred instantiation:

$$\mu_t = \mathrm{clip}(\alpha \Delta E_t + \beta \|\Omega_t\|, \mu_{\min}, \mu_{\max}).$$

Third, an operational spin estimator computes the antisymmetric component of a local gradient field. In the preferred embodiment, operational spin is computed as:

$$\Omega_t = (mu \nabla J_t),$$

or, where direct jerk estimation is impractical,

$$\Omega_t = (mu \nabla u_t).$$

For graph-based systems, ∇ denotes a discrete gradient over edges or neighborhoods, and $(mu \cdot)$ is implemented as the antisymmetric component of the local Jacobian or update matrix.

Fourth, an Adaptive Dissipative Response (ADR) layer implements ΔE as a measurable regulation signal that modulates dissipation strength. In the best mode, ΔE_t is computed as a bounded scalar functional combining one or more of: (i) variance of recent outputs or residuals, (ii) magnitude of operational spin $\|\Omega_t\|$, (iii) jerk energy proxies, and (iv) coherence deviation measures. Typical operating ranges for normalized ΔE_t are in $[0, 1]$.

The adaptive dissipation coefficient μ_t is then computed as:

$$\mu_t = \mathrm{clip}(\alpha\, \Delta E_t + \beta\, \|\Omega_t\|,\ \mu_{\min},\ \mu_{\max}),$$

where $\mu_{\min} \in [0.05, 0.2]$, $\mu_{\max} \in [0.6, 1.0]$, and α, β are tunable gains selected based on system responsiveness and noise characteristics.

Residual spin is updated according to:

$$\tilde{\Omega}_{t+1} = (1 - \mu_t)\tilde{\Omega}_t + \mu_t \Phi_t,$$

where Φ_t is a bounded, coherence-preserving target spin estimate derived from constraints or smoothed environmental response.

Fifth, drift is accumulated as:

$$D_t = D_{t-1} + \|\tilde{\Omega}_t\|_{\mathrm{res}},$$

with D_t optionally normalized or discounted over time. In the preferred embodiment, a drift threshold $D_{\max}$ is defined in the range $[1, 10]$ (normalized units), such that when $D_t > D_{\max}$, feedback is triggered to tighten directional constraints, increase dissipation, or temporarily restrict admissible updates.

This best mode has been validated in simulation and analytic studies to maintain coherence under turbulence, delay, and repeated perturbations, while remaining responsive to directional intent encoded via the constraint operator. The described implementation is not intended to limit the scope of the invention, but represents the currently preferred and most robust realization of the disclosed architecture.

5. Drift Accumulation as Residual Spin Integration

Residual spin not eliminated by ADR accumulates across time and appears as structural drift. One embodiment defines drift:

$$D_t = \sum_{k=0}^{t} \left\| \tilde{\Omega}_k \right\|_{\mathrm{res}}.$$

Other embodiments may define drift as: a) a discounted sum, b) a running average, c) an integral approximation, d) a coherence-loss signal, or e) a bounded risk functional that combines residual spin with control energy or error.

The disclosed architecture uses drift as a measurable signature of non-recovered deformation in the adaptive process.

6. Spin-Drift Correspondence (Hypothesis / Working Principle)

In many practical settings, it is useful to treat drift growth as bounded by the time-integral (or sum) of residual spin magnitude:

$$D_t \lesssim C \sum_{k=0}^{t} \left\| \tilde{\Omega}_k \right\|,$$

where C is an application-dependent constant absorbing smoothness, stability, or dissipation parameters of the medium.

This relationship is presented as a working correspondence useful for design and validation. It is not asserted as a universal physical law; rather, it provides a structural bridge between measurable antisymmetric deformation and cumulative degradation.

More precisely, C can be taken to absorb a coarse Lipschitz bound that links residual spin to changes in the update operator F_t, together with effective dissipation parameters of the medium.

Example (linear time-varying case). As a simple example, consider a linear time-varying system where the update operator can be written as $F_t(x) = A_t x$ with uniformly bounded operator norm $\|A_t\| \leq L$ for all t. In this case, changes in F_t can be bounded in terms of a Lipschitz constant on the family $\{A_t\}_t$, and C can be chosen proportional to this bound, modulated by the effective dissipation rate of the medium. This shows that in standard linear settings C is not an arbitrary constant, but can be related directly to familiar stability and smoothness parameters. For clarity, the disclosed architecture does not require the above bound to hold exactly; drift may be accumulated directly from residual spin by definition, while the correspondence serves as an engineering upper-bound and calibration guideline rather than a dependency.

7. Distinguishing Parametric Tuning from Structural Operator Evolution

Many adaptive controllers and many reinforcement learning systems adjust parameters under a fixed rule, even when the parameter space is large. In such cases, the adaptation is "parametric" in the sense that the form of the update operator remains fixed.

The disclosed framework supports a sharper distinction. Let the system update be:

$$S_{t+1} = F_t(S_t, u_t, E_t).$$

Parametric tuning corresponds to F_t remaining in a fixed operator class with a fixed update mechanism, while structural evolution corresponds to the operator class or its effective representational structure evolving.

Structural evolution may be recognized when the system's adaptation modifies the rule family itself, e.g.:

$$F_{t+1} = G(F_t, \Delta S_t),$$

where G changes not only scalar gains but also the structure by which updates are computed. This includes cases where the effective representational capacity or organizational depth changes over time.

This distinction also addresses meta-learning and meta-RL settings: a system may be considered structurally evolving if its adaptation mechanism modifies the rule family (or its representational structure) in a sustained, self-maintaining manner, rather than merely tuning parameters under a fixed meta-update.

8. Minimal Demonstrator (Toy Simulation) and Predictive Role of the Stack

The disclosed architecture admits a minimal toy demonstrator that separates constraints, ADR regulation, and environment geometry.

As a minimal toy demonstrator, consider a simulated agent evolving in a stochastic field E_t with curvature penalties. Let: (i) the directional constraint operator define a risk-bounded admissible trajectory set, (ii) the ADR regulator process operational spin using adaptive μ_t, and (iii) the environment implement turbulence by modulating jerk and variance statistics.

Such systems exhibit distinct attractors when the constraint operator is varied while ADR remains fixed, illustrating the predictive role of the architecture: changes in admissible directionality alter long-term stable regimes even under unchanged dissipative regulation.

This toy model does not aim at realism; its purpose is to make explicit how directional constraints, spin regulation, and environment geometry can be separated and manipulated independently in a controlled setting.

Pseudocode Summary of the Adaptive Regulation Cycle

```
for each time step t:
    observe state S_t and environment E_t
    u_t = W_DC(S_t, E_t)
    compute J_t from differences in u_t or S_t
    Omega_t = skew(grad(J_t))
    mu_t = f(variance_t, jerk_t, E_t)
    Omega_res = (1 - mu_t) * Omega_prev + mu_t * Phi_t
    D_t += norm(Omega_res)
    if D_t exceeds threshold:
        adjust constraints or regulation parameters
end for
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9. Measurement and Operationalization Across Domains

The disclosed method is operational: it defines what can be measured.

In physical media, operational spin may be computed from velocity-like fields or measured gradients using antisymmetric decomposition.

In cybernetic systems, u_t, J_t, and Ω_t may be computed from local gradients of traffic, load, belief, or policy fields across a network graph, using discrete analogs of gradient and antisymmetric components.

In learning systems, operational spin may be computed from gradients in parameter-update fields or from antisymmetric components in local Jacobians of update dynamics.

Drift may be measured as accumulated residual spin, coherence loss, or deviation in stability signatures.

10. Advantages

The disclosed architecture provides multiple advantages over systems that only minimize scalar error.

It offers an explicit representation of rotational deformation induced by directional perturbations. It separates admissible directionality from dissipative correction. It provides drift metrics tied to residual deformation. It supports stability and auditability under uncertainty, delay, noise, and adversarial conditions. It provides a design language for building coherence-preserving adaptive systems without requiring metaphysical assumptions.

11. Limitations and Scope

The disclosed framework is structural and applies most directly when the system admits a state field or representation where gradient-like quantities can be computed (continuously or discretely). The spin–drift correspondence is a useful working relationship and may require calibration per domain. The directional constraint operator can be implemented in multiple ways; the disclosure covers such implementations without requiring a specific philosophical interpretation.

12. EXEMPLARY EMBODIMENTS

Example 1: Adaptive Physical Controller

Inputs: system state S_t, environment field E_t. Steps:

1. Apply directional constraint operator W_{DC} to restrict admissible actuation directions.
2. Generate directional control input u_t.
3. Compute jerk field J_t from temporal differences of u_t.
4. Estimate operational spin $\Omega_t = (mu\nabla J_t)$.
5. Apply ADR using adaptive coefficient μ_t to obtain residual spin $\tilde{\Omega}_t$.
6. Accumulate drift D_t and adjust constraint strength if D_t exceeds a threshold.

Example 2: Cybernetic / Networked System

Inputs: network load field, anomaly scores, risk constraints. Steps:

1. Directional constraints encode admissible routing or response actions.
2. Operational spin is computed from antisymmetric components of gradients in load or anomaly fields.
3. ADR smooths oscillatory or torsional response components.
4. Drift accumulation signals persistent structural stress and triggers policy adjustment.

Example 3: Learning or Reinforcement Learning System

Inputs: policy parameters, update gradients, environment feedback. Steps:

1. Directional constraints restrict policy updates to preserve invariants.
2. Compute operational spin from antisymmetric components of local update Jacobians.
3. Apply ADR to suppress destructive oscillations in learning dynamics.
4. Drift accumulation indicates structural instability and gates future updates.

Directional Constraint Operator
$\downarrow$
Directed Perturbation / Jerk Field
$\downarrow$
Operational Spin Estimator
$\downarrow$
Adaptive Dissipative Response (ΔE)
$\downarrow$
Residual Spin and Drift Accumulation
$\downarrow$
Feedback to Constraints / Regulation

Figure 4: Block diagram illustrating the layered adaptive regulation architecture.

Initial isotropic field $\rightarrow$ directional perturbation
$\rightarrow$ skewed gradient $\rightarrow$ localized rotational response (spin)

Figure 5: Heuristic illustration of isotropy breaking leading to operational spin.

Residual Spin Magnitude $\|\tilde{\Omega}_t\|$ accumulated over time
$\rightarrow$ Drift D_t
$\rightarrow$ Threshold $D_{\max}$ triggers feedback

Figure 6: Illustrative relationship between residual spin accumulation and drift-based feedback.

13. OPTIONAL CLAIM-LIKE STATEMENTS

While claims are not required in a provisional filing, the following statements indicate intended scope.

1. A method of regulating an adaptive system comprising applying a directional constraint operator to restrict admissible trajectories, computing operational spin as an antisymmetric component of a gradient field induced by a directional perturbation, applying adaptive dissipative response to reduce residual spin, computing drift as a cumulative metric of residual spin, and feeding back drift to modify constraints or regulation intensity.

2. The method of statement 1 wherein operational spin is computed as $\Omega_t = (mu\nabla J_t)$ or $\Omega_t = (mu\nabla u_t)$.

3. The method of statement 1 wherein the adaptive dissipation coefficient μ_t increases under increased variance or jerk and decreases under stable conditions.

4. A system configured to perform the method of any of the preceding statements.

5. A non-transitory computer-readable medium storing instructions that, when executed by one or more processors, cause the one or more processors to perform the method of any of the preceding statements, including application of a directional constraint operator, computation of operational spin as an antisymmetric component of a gradient field, adaptive dissipative response regulation, drift accumulation, and feedback-based modification of constraints or regulation parameters.

6. The system of statement 4, wherein the system is implemented as a distributed or multi-agent system comprising a plurality of interacting agents, each agent configured to locally compute operational spin, apply adaptive dissipative response, and contribute to a global or hierarchical drift accumulation metric governing collective adaptation.

7. A non-transitory computer-readable medium storing instructions that, when executed by one or more processors, cause an adaptive system to: a) apply a directional constraint operator to restrict admissible trajectories or updates; b) compute operational spin as an antisymmetric component of a gradient field induced by directional perturbations; c) apply an adaptive dissipative response to reduce residual operational spin based on a computed ΔE signal; d) accumulate drift as a function of residual spin over time; and e) modify constraint strength or regulation intensity when accumulated drift exceeds a threshold.

8. The non-transitory computer-readable medium of the preceding statement, wherein the instructions are executed in a distributed or multi-agent system comprising a plurality of interacting agents or nodes.

9. The non-transitory computer-readable medium of the preceding statement, wherein each agent computes a local operational spin estimator based on local gradients or interactions, and wherein drift accumulation is computed locally, globally, or hierarchically across agents.

10. A distributed adaptive system comprising: a) a plurality of agents, each having a local state representation and a local directional constraint operator; b) at least one operational spin estimator configured to compute antisymmetric components of local update or interaction fields; c) an adaptive dissipative response layer implementing ΔE to regulate residual spin; and d) a drift accumulation mechanism configured to gate or modify future updates across the system based on accumulated residual deformation.

11. The distributed adaptive system of the preceding statement, wherein the agents communicate via graph-based, message-passing, or field-based interactions, and wherein operational spin is computed using discrete gradient or Jacobian approximations on the interaction graph.