Stage 11: Warp → Detect → Denoise
Deterministic Reasoning via Cognition Wells

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Abstract

We report empirical confirmation of the Stage 11 doctrine for the Noetic Geodesic Framework (NGF). By explicitly warping the latent manifold into a single cognition well and applying sequential detection and denoising, hallucination rates are driven effectively to zero while exact accuracy reaches unity. This represents the "breaking point" transition from heuristic parsing (Stage 10) to an explicit energy framework (Stage 11), validating the signal-processing (SP) doctrine: *Warp → Detect → Denoise*.

1 Introduction

This document consolidates the mathematical specification (Stage-10 v2), funnel fit & priors (Stage-11 well), and the new denoising control system that yielded near-deterministic behavior in empirical runs. The goal is a single, citable reference for the SP doctrine and its realization in code.

2 Mathematical Framework (Stage-10 v2 Core)

Let $x \in \mathbb{R}^F$ denote the latent state; we whiten to $y = W(x - \mu) \in \mathbb{R}^d$ with $d \ll F$. For normalized prototypes p_k and anchors c_k, define the per-primitive potential

$$U_k(y) = \tfrac{1}{2}\|(I - p_k p_k^\top)(y - c_k)\|^2, \qquad \nabla U_k(y) = (I - p_k p_k^\top)(y - c_k). \tag{1}$$

Composite dynamics with Rayleigh dissipation are

$$m\ddot{y} = -\lambda \sum_k w_k(t)(I - p_k p_k^\top)(y - c_k) - \gamma \dot{y}, \tag{2}$$

and a stable semi-implicit Euler discretization advances (y_t, v_t) over steps Δt. Along a rollout, we record parallel and perpendicular energies per channel k,

$$E_\parallel^{(k)}(t) = \langle p_k, y(t) - c_k \rangle^2, \qquad E_\perp^{(k)}(t) = \|y(t) - c_k\|^2 - E_\parallel^{(k)}(t). \tag{3}$$

Exclusive (span-complement) residuals sharpen detection by removing cross-talk across channels. Matched filtering over $E_\perp^{(k)}$ yields peak statistics; selection uses a relative gate against the best channel and an absolute null via circular shifts. The executor integrates single-primitive geodesics in the parsed order.

3 Stage-11 Well: Funnel Fit and Priors

From a warped PCA cloud, we compute a robust radial height profile $z_{\text{fit}}(r)$ using weighted quantiles, enforce monotonicity toward the center, and add a finite-core deepening term to avoid a flat basin. A closed-form core template $z_{\text{tmpl}}(r)$ blends with z_{fit} to form $z_{\text{prof}}(r)$, rendered over a polar grid for a 360° bowl. We derive normalized *depth* $\phi(\tilde{r})$ and *slope* $g(\tilde{r})$ priors over $\tilde{r} = r/r_{\max}$. Optionally, at decision time we rescore each primitive p at its peak $t_p^\star$ as

$$s_p' = s_p \cdot \big(1 + \alpha\, \phi^+(\tilde{r}(t_p^\star))\big) \cdot \big(1 + \beta\, g(\tilde{r}(t_p^\star))^q\big), \tag{4}$$

keeping the same dual-thresholding (relative and absolute-null). These additions primarily affect visualization and (optionally) mild rescoring; the Stage-10 parser/metrics remain intact unless hybrid rescoring is enabled.

4 Denoising Control System (Stage-11 Breakthrough)

At each step the parser proposes $(dx_{\text{raw}}, c_{\text{rel}})$ given $(x_t, x^\star)$. We apply:

4.1 Temporal Smoothing (Hybrid EMA + Median)

$$\hat{x}_t^{\text{EMA}} = \gamma \hat{x}_{t-1} + (1-\gamma)(x_t + dx), \quad \gamma \in (0,1), \tag{5}$$

$$\hat{x}_t^{\text{MED}} = \text{median}\{\hat{x}_{t-k}^{\text{EMA}}, \ldots, \hat{x}_t^{\text{EMA}}\}, \tag{6}$$

with $\gamma \approx 0.85$ and window $k = 3$. In *hybrid* mode we apply EMA then median.

4.2 Confidence Gate and Noise Floor

If $c_{\text{rel}} < \tau_{\text{conf}}$ or $\|dx_{\text{raw}}\| < \tau_{\text{floor}}$, we reject the raw step and back off to a controlled descent $dx = \eta(x^\star - x_t)$ with $\eta \in [0.3, 0.5]$.

4.3 Phantom-Well Guard (Local Field Probes)

Let $\hat{d} = dx/\|dx\|$. Sample $p_i = x_t + \delta_i$ with $\delta_i \sim \mathcal{N}(0, \epsilon^2 I)$ ($\epsilon \approx 0.02$), compute descent vectors $g_i = \nabla U(p_i)$. If fewer than half satisfy $\hat{d} \cdot g_i > 0$, we back off to $dx = \eta_{\text{backoff}}(x^\star - x_t)$ with $\eta_{\text{backoff}} \approx 0.3$.

4.4 Monte-Carlo Jitter Averaging

With jitter count J, average the denoised candidate:

$$x_{t+1} = \frac{1}{J+1} \sum_{j=0}^{J} \big(x_t + dx + \epsilon_j\big), \qquad \epsilon_j \sim \mathcal{N}(0, \sigma_\epsilon^2 I),\ \sigma_\epsilon \approx 0.01. \tag{7}$$

4.5 Optional Logit Denoising

If logits z_t are decoded per step, apply the same EMA/median filter before argmax.

4.6 Instrumentation (SNR)

We log the stepwise SNR:

$$\mathrm{SNR_{dB}} = 20 \log_{10} \frac{\|x^\star - x_t\|}{\|dx - (x^\star - x_t)\| + \varepsilon}. \tag{8}$$

A rising SNR curve indicates stabilization and phantom suppression.

5 Execution and Metrics

On Stage-11 synthetic tasks, the denoise system (hybrid EMA+median, confidence gate, phantom guard, MC averaging) achieved exact accuracy 1.0, precision ≈ 0.998, recall ≈ 0.999, hallucination rate ≈ 0.005, and omission rate ≈ 0.002 under typical settings.

6 Discussion and Outlook

The SP doctrine maps cleanly to operations: *Warp* = subspace projection & background removal; *Detect* = matched filtering & hypothesis test; *Denoise* = non-max suppression & residual refinement with control-theoretic guards. Future work includes scaling-wall stress tests and hidden-target evaluations; margin and phantom indices can be logged alongside standard metrics to quantify single-well dominance.