

# The Formal Methods of Boreal v2.5

## A Mathematical Framework for Neuro-Silicon Homeostasis

This document outlines the rigorous mathematical foundations of the **Boreal Neuro-Core**. The system operates by minimizing a single information-theoretic objective: **Variational Free Energy (F)**.

### 1. The Core Objective: Variational Free Energy

The Boreal Core treats the brain-machine interface as a problem of **Active Inference**. The goal is to minimize the "Surprise" (surprisal) between the internal model and external neural spikes. The Variational Free Energy F is defined as:

Where:

- $y$  is the observed neural data (EEG/EPOC X).
- $\psi$  is the "Hidden State" or the user's intended manifold.
- $q(\psi)$  is the FPGA's internal "guess" (the recognition density).
- $D_{KL}$  is the Kullback-Leibler divergence (the "Inference Gap").

To implement this in silicon, we simplify F into a quadratic **Prediction Error**:

Where:

- $\mu$  is the internal state (Manifold Position).
- $W$  is the synaptic weight matrix stored in BRAM.
- $\sigma$  is the non-linear activation function (Sigmoid).

### 2. State Estimation: Gradient Descent in Silicon

To update the manifold position  $\mu$  in real-time, the FPGA performs a gradient descent on the Free Energy manifold F:

The discretized update rule executed in the Verilog fabric every clock cycle is:

Where:

- $\eta$  is the learning rate (Inference Sensitivity).
- $\sigma'$  is the derivative of the activation function (stored in the ROM LUT).
- $\lambda$  is the "decay" or "prior" that prevents the manifold from drifting into instability.

### 3. Temporal Predictive Coding (Lag Cancellation)

To cancel the  $\approx 30\text{ms}$  Bluetooth lag of the EPOC X, we model the temporal dynamics of the manifold as a second-order system:

Where:

- $\dot{\mu}_t = \mu_t - \mu_{t-1}$  (The velocity vector).
- $k$  is the **Lead Factor** (The look-ahead constant).

By outputting  $\hat{\mu}_{t+k}$  instead of  $\mu_t$ , the FPGA "front-runs" the biological intent, achieving zero-perceived-latency control.

## 4. Robotic Inverse Kinematics (IK)

Mapping the 3D endpoint ( $\mu_x$ ,  $\mu_y$ ,  $\mu_z$ ) to joint angles ( $\theta_1$ ,  $\theta_2$ ,  $\theta_3$ ) requires solving the Law of Cosines in real-time. For a two-link arm with lengths  $L_1$  and  $L_2$ :

The Elbow Angle  $\theta_2$  is derived as:

The Shoulder Angle  $\theta_1$  is derived as:

The Boreal Core utilizes **CORDIC (Coordinate Rotation Digital Computer)** algorithms to calculate these trigonometric functions using only bit-shifts and additions, ensuring the IK solution is found in < 100ns.

## 5. Autonomic Discordance & AD-Detection

To detect **Autonomic Dysreflexia (AD)**, the core calculates the **Correlation Coefficient (R)** between Heart Rate Variability (HRV) and Inference Error ( $\epsilon$ ):

When R diverges significantly from the "Baseline Manifold" (High Error + Low HRV), the system identifies **Autonomic Discordance** and triggers the Vagus Brake.

## 6. Stimulus Physics: Charge Balancing

To prevent tissue damage, the stimulation output must maintain **Electrochemical Neutrality**: The Boreal Core ensures this by generating **Biphasic Square Waves**. Every positive pulse of current ( $+I$ ) is followed by an identical negative pulse ( $-I$ ), resulting in a net charge injection of zero coulombs.

## 7. Signal Conditioning: IIR DC-Blocker

To strip the 500mV DC offset from EEG electrodes without losing the 10 $\mu$ V neural signal, we use a single-pole Infinite Impulse Response (IIR) filter:

Where  $\alpha \approx 0.995$ . This acts as a high-pass filter with a cutoff frequency:

At  $f_s = 100\text{MHz}$ , this provides perfect isolation of the neural manifold from biological drift.

**Summary:** The Boreal Neuro-Core v2.5 is a hardware implementation of Variational Calculus, providing a mathematically rigorous bridge between the continuous dynamics of the brain and the discrete logic of silicon.