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# A stabilization approach to improve decoding performance using non-linear dynamical models

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*Introduction:* One of the key challenges in developing Brain-Computer Interfaces (BCIs) is the presence of noise in recorded neural signals. Such noise may result from the recording hardware or from fluctuations in the subject's internal state, both of which can occur independently of the intended motor command. To address this issue, we propose leveraging accurate predictions from nonlinear functional models of neuronal dynamics to extract a stabilized control signal for the interface.

*Material, Methods and Results:* This study was conducted using recordings from the primary motor cortex of non-human primates performing an 8×8 reaching task with simultaneous measurements of kinematic signals (finger position) and neural activity [1]. To infer the neuronal dynamics, we employed a shallow Piecewise Linear Recurrent Neural Network (sh-PLRNN) [2]. This architecture consists of two principal components: a latent model, which captures the temporal evolution of the underlying latent dynamical process $z(t)$, and an observational model, which captures how the latent representations affect the recorded neural activity $x(t)$.

Building on this framework, we introduced a stabilization approach aimed at reducing noise in the recorded neural data. As illustrated in Fig.*1A*, we use the inferred nonlinear sh-PLRNN model to generate multiple predictions of the latent state $z(t)$ based on the neuronal activity $x$ recorded in a time window between $t-T$ and $t-1$. While these predictions estimate the latent state at the same time $t$, each is influenced by independent noise realizations, and can be combined to obtain a signal with lower noise variance.

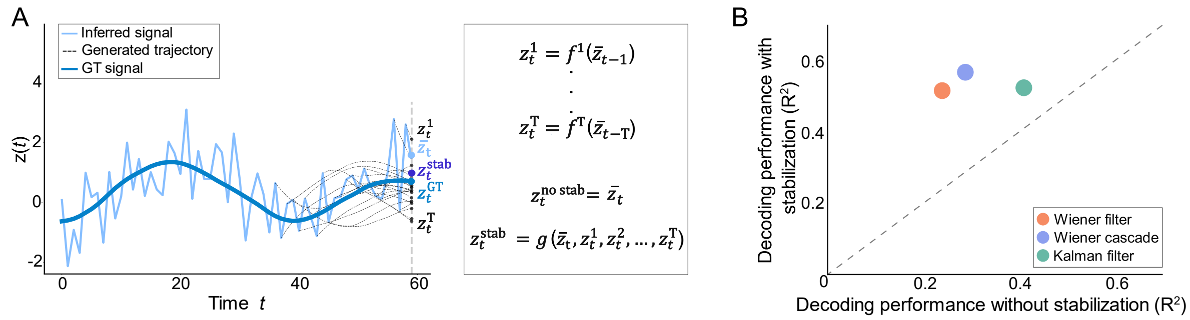


*Figure 1:* ***Stabilization approach for BCI:*** *(A) Schematic representation of the stabilization rationale. At each time t, the latent neural state $z_t$ can be inferred directly from the recorded activity $x_t$, as $\bar{z}_t$ (in light blue), as well as from the past recordings $x_{t-\tau}$ through the inferred latent dynamics map $f$, as $z_t^\tau = f^\tau(\bar{z}_{t-\tau})$ (in black). By combining predictions from multiple past steps, $\tau = 0 \dots T$, we can then derive an estimate of the ongoing neuronal state $z_t^{stab}$ which better approximates the ground truth state $z_t$ (blue) than $\bar{z}_t$. (B) Decoding results. Scatter plot comparing decoding performances with or without stabilization for three types of decoders.*

To test the general applicability of this approach, we employed here three different decoders to estimate from the latent state $z(t)$ the monkey finger's position: the Wiener filter, the Wiener cascade, and the Kalman filter (Fig.*1B*). Our results show that the proposed stabilization approach improves decoding accuracy. This method provides a scalable solution for stabilizing noisy recordings, thus favoring a more precise and stable BCI control.

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