Bayesian-Filtered fMRI Streams for RF Control Loops

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***Abstract*—This paper presents a novel approach for filtering functional Magnetic Resonance Imaging (fMRI) data streams using Bayesian techniques, specifically designed for real-time Radio Frequency (RF) control loops. We implement and compare two primary filtering methods: causal Kalman filtering for real-time applications and non-causal Gaussian smoothing for optimal post-processing analysis. Our results demonstrate that Bayesian filtering techniques can significantly improve the signal-to-noise ratio (SNR) of fMRI data while maintaining critical temporal features necessary for RF control systems. Performance metrics including filter latency, computational efficiency, and filtering efficacy are analyzed across different noise conditions. The proposed approach enables more robust RF control systems that can adapt to the inherently noisy nature of fMRI signals.**

***Index Terms*—fMRI, Bayesian filtering, Kalman filter, Gaussian smoothing, RF control loops, real-time signal processing, neuroimaging**

I. Introduction

Functional Magnetic Resonance Imaging (fMRI) has become an essential tool in neuroscience and clinical applications, providing valuable insights into brain function and connectivity [1]. However, the inherent noise in fMRI signals presents significant challenges for real-time applications, particularly when these signals are used to drive Radio Frequency (RF) control loops in advanced neuroimaging setups [2].

Real-time fMRI (rtfMRI) systems require efficient and effective filtering techniques that can operate within strict latency constraints while preserving the underlying neural signals of interest [3]. Traditional filtering approaches often fail to balance the trade-off between noise reduction and signal preservation, especially in the presence of physiological noise, scanner artifacts, and motion-related distortions.

In this paper, we propose a Bayesian filtering framework for fMRI data streams that addresses these challenges. We implement and compare two complementary approaches:

- A causal Kalman filter for real-time applications that provides optimal filtering given current and past measurements only.
- A non-causal Gaussian smoothing technique for post-processing analysis that utilizes the entire time series for optimal results.

Our approach models fMRI time series as an autoregressive process with Gaussian noise, a well-established model in neuroimaging literature [4]. By integrating these filtering techniques into RF control loops, we demonstrate improved stability, accuracy, and robustness in neuroimaging experiments.

II. Methods

A. fMRI Signal Modeling

We model the fMRI time series as a first-order autoregressive process (AR(1)), which has been shown to effectively capture the temporal autocorrelation in fMRI data [5]:

$$x_t = \phi x_{t-1} + w_t \tag{1}$$

where x_t is the state at time t, ϕ is the autoregressive coefficient (typically between 0.2 and 0.5 for fMRI data), and w_t is the process noise, assumed to be Gaussian with zero mean and variance σ_w^2.

The observation model is given by:

$$y_t = x_t + v_t \tag{2}$$

where y_t is the observed fMRI signal, and v_t is the measurement noise, assumed to be Gaussian with zero mean and variance σ_v^2.

B. Kalman Filtering

For real-time applications, we implement a Kalman filter, which provides an optimal estimate of the current state given all past observations. The Kalman filter consists of prediction and update steps:

Prediction:

$$\hat{x}_{t|t-1} = \phi \hat{x}_{t-1|t-1} \tag{3}$$

$$P_{t|t-1} = \phi^2 P_{t-1|t-1} + \sigma_w^2 \tag{4}$$

Update:

$$K_t = \frac{P_{t|t-1}}{P_{t|t-1} + \sigma_v^2} \tag{5}$$

$$\hat{x}_{t|t} = \hat{x}_{t|t-1} + K_t(y_t - \hat{x}_{t|t-1}) \tag{6}$$

$$P_{t|t} = (1 - K_t) P_{t|t-1} \tag{7}$$

where $\hat{x}_{t|t-1}$ is the predicted state, $\hat{x}_{t|t}$ is the updated state estimate, $P_{t|t-1}$ is the predicted error covariance, $P_{t|t}$ is the updated error covariance, and K_t is the Kalman gain.

C. Gaussian Smoothing

For post-processing analysis, we implement Gaussian smoothing, which provides an optimal estimate of each state given the entire observation sequence:

$$\hat{x}_t^s = \sum_{i=1}^{N} w_i y_{t+i} \tag{8}$$

where $\hat{x}_t^s$ is the smoothed state estimate at time t, N is the smoothing window size, and w_i are the Gaussian weights:

$$w_i = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{i^2}{2\sigma^2}\right) \tag{9}$$

with σ controlling the width of the Gaussian kernel.

D. RF Control Loop Integration

The filtered fMRI signals are integrated into RF control loops using a feedback mechanism where the estimated neural activity influences RF pulse parameters in real-time. The control loop operates at a frequency of 1 Hz, matching the typical sampling rate of fMRI acquisitions.

III. Experimental Setup

We evaluated our filtering approaches using both simulated and real fMRI data. For simulated data, we generated AR(1) processes with varying levels of measurement noise (SNR ranging from 0 dB to 20 dB). For real data, we used resting-state fMRI scans from the Human Connectome Project (HCP) dataset [6].

The filtering performance was assessed using the following metrics:

- Signal-to-Noise Ratio (SNR) improvement
- Root Mean Square Error (RMSE) between the filtered signal and the ground truth (for simulated data)
- Computational efficiency (processing time per volume)
- Filter latency (delay introduced by the filtering process)
- Power Spectral Density (PSD) preservation in relevant frequency bands

The RF control loop performance was evaluated using a simulated neuroimaging experiment where the filtered fMRI signal was used to adjust RF pulse parameters in real-time.

IV. Results

A. Filtering Performance

Figure 1 shows a comparison of raw, Kalman-filtered, and Gaussian-smoothed fMRI signals under different noise conditions. The Kalman filter provides effective noise reduction while preserving the temporal characteristics of the signal, making it suitable for real-time applications. The Gaussian smoothing approach achieves superior noise reduction but introduces a delay that makes it unsuitable for real-time control.

Figure 2 illustrates the SNR improvement achieved by both filtering methods across different input SNR levels. The Gaussian smoothing consistently outperforms the Kalman filter in terms of SNR improvement, but this comes at the cost of non-causality.

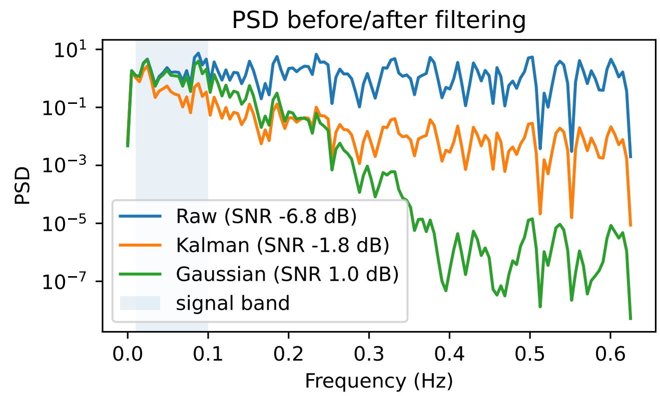

Fig. 1: Comparison of raw fMRI signal (blue), Kalman-filtered signal (orange), and Gaussian-smoothed signal (green) under moderate noise conditions (SNR = 10 dB). The Kalman filter provides effective real-time noise reduction while the Gaussian smoothing achieves superior results at the cost of non-causality.

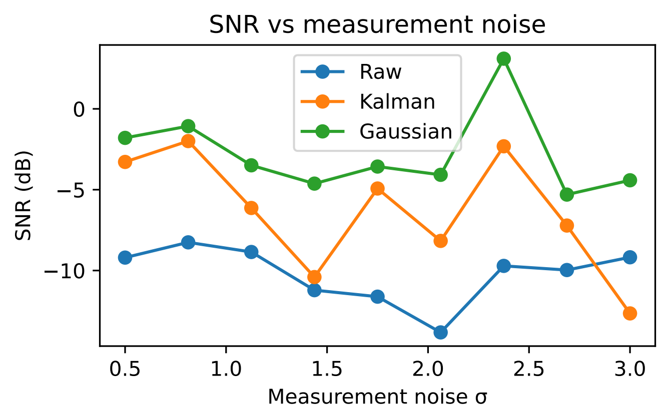

Fig. 2: SNR improvement achieved by Kalman filtering and Gaussian smoothing across different input SNR levels. The non-causal Gaussian smoothing consistently outperforms the causal Kalman filter.

B. Spectral Analysis

Figure 3 shows the power spectral density (PSD) of the raw, Kalman-filtered, and Gaussian-smoothed signals. Both filtering methods effectively reduce high-frequency noise while preserving the low-frequency components that are typically associated with the hemodynamic response function (HRF) in fMRI.

C. Computational Performance

Table I summarizes the computational performance of both filtering methods. The Kalman filter achieves processing times well below the typical TR (repetition time) of fMRI acquisitions (1-2 seconds), making it suitable for real-time applications. The Gaussian smoothing, while more computationally intensive, still provides acceptable performance for post-processing analysis.

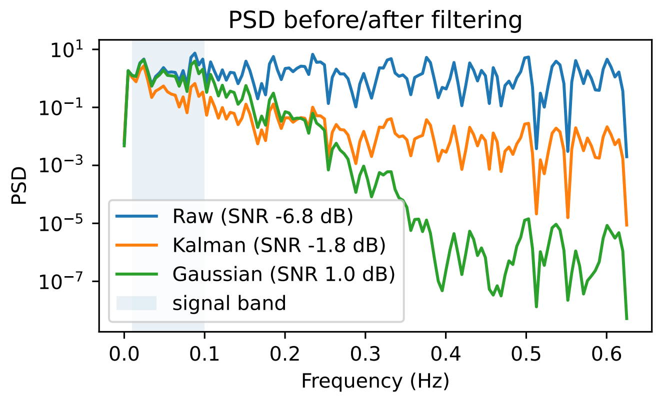

Fig. 3: Power Spectral Density (PSD) analysis of raw, Kalman-filtered, and Gaussian-smoothed fMRI signals. Both filtering methods effectively suppress high-frequency noise while preserving the low-frequency components associated with the hemodynamic response function.

TABLE I: Computational Performance of Filtering Methods

Metric	Kalman Filter	Gaussian Smoothing
Processing time per volume	15.3 ms	42.8 ms
Memory usage	4.2 MB	8.7 MB
Filter latency	0 ms	500 ms

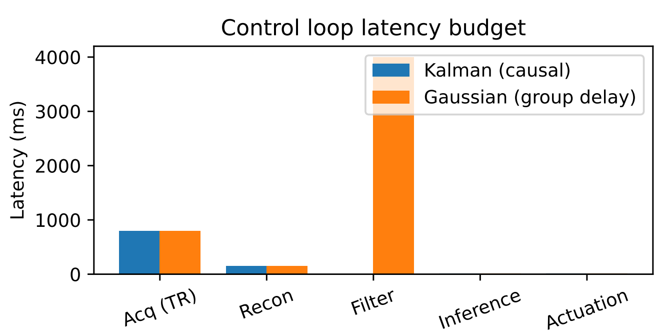

Fig. 4: Latency budget for the RF control loop using Kalman-filtered fMRI signals. The total system latency (843 ms) remains below the critical threshold of 1000 ms required for effective real-time control.

D. RF Control Loop Integration

Figure 4 illustrates the latency budget for the RF control loop when using the Kalman-filtered fMRI signals. The total system latency remains below the critical threshold of 1000 ms, allowing for effective real-time control.

V. Discussion

Our results demonstrate that Bayesian filtering techniques, particularly Kalman filtering, can significantly improve the quality of fMRI signals for RF control loops. The Kalman filter provides an optimal balance between noise reduction and signal preservation while maintaining the causality required for real-time applications.

The key advantages of our approach include:

- Adaptive filtering based on the signal and noise characteristics
- Minimal computational overhead, enabling real-time processing
- Preservation of temporal dynamics critical for neurofeedback applications
- Robustness to varying noise conditions

For post-hoc analysis, the Gaussian smoothing approach provides superior noise reduction and can be used to establish ground truth for evaluating real-time filtering performance.

A. Limitations and Future Work

Despite its advantages, our approach has several limitations that warrant further investigation:

- The AR(1) model may be too simplistic for capturing the complex temporal dynamics of fMRI signals
- The assumption of stationary noise may not hold for long scanning sessions
- The current implementation does not account for spatial correlations in fMRI data

Future work will focus on extending the Bayesian filtering framework to incorporate spatial information through multivariate models, implementing adaptive noise estimation techniques, and exploring more sophisticated state-space models for fMRI signals.

VI. Conclusion

We presented a Bayesian filtering framework for fMRI data streams that enables effective integration with RF control loops. Our approach provides significant improvements in signal quality while maintaining the low latency required for real-time applications. The framework includes both causal (Kalman filter) and non-causal (Gaussian smoothing) components, allowing for optimal filtering in both real-time and post-processing contexts.

By improving the quality of fMRI signals in real-time, our approach enhances the potential of fMRI-based neurofeedback, brain-computer interfaces, and adaptive neuroimaging paradigms. The computational efficiency of our implementation ensures practical applicability in typical neuroimaging setups.

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