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ESTIMATION OF STRUCTURAL DISPLACEMENTS FROM MEASURED ACCELERATIONS VIA GAUSSIAN PROCESS REGRESSION

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Abstract. *In the context of Structural Health Monitoring, displacement responses can be informative on the structural performance when combined with virtual sensing techniques or when compared to numerical analyses. Unfortunately, traditional displacement sensors are often expensive, limited in sampling frequency, and prone to low signal-to-noise ratios. In contrast, accelerometers are cost-effective, capable of high-rate sampling, and generally associated with higher signal-to-noise ratios, and can therefore be used for estimating displacements. However, estimating displacements from acceleration measurements through numerical double integration presents significant challenges: measurement noise in the low-frequency range becomes amplified, causing drift and distortion that can render displacement estimates unreliable. This can be particularly problematic for structures exhibiting low-frequency responses. This study presents a methodology for estimating structural displacements from noisy acceleration measurements using Gaussian Process (GP) regression in state space form. GP regression enables Bayesian inference with physically informed priors in the form of displacement magnitude and zero-mean assumptions. Additionally, uncertainty in the estimated displacements is quantified, providing not only point estimates but also credible intervals given the specified kernel hyperparameters. The method is validated through numerical examples of offshore structures subjected to wave loads.*

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1 INTRODUCTION

This study deals with the problem of estimating structural displacements from measured accelerations, which is relevant for structural health monitoring and performance assessment. Displacement responses can provide valuable information on the structural behavior, for example in the context of virtual sensing. However, traditional displacement sensors are often expensive, limited in sampling frequency, and prone to low signal-to-noise ratios. On the other hand, accelerations sensors are cost effective and capable of high-rate sampling, but numerical double integration, needed to move from accelerations to displacements, amplifies low-frequency noise, causing drift. Existing methods for alleviating this issue exist, such as frequency-domain integration with high-pass filtering [1] or polynomial detrending. However, they require manual parameter tuning and do not provide uncertainty quantification. When low-rate displacement measurements are available, multi-rate Kalman filter approaches have been also proposed [2], but these do not allow for the incorporation of prior information.

This paper applies the methodology for displacement estimation recently introduced in [3], which builds on Gaussian process (GP) regression in state space form developed by Hartikainen and Särkkä in [4]. GP regression is performed via Kalman filtering and Rauch-Tung-Striebel (RTS) smoothing, achieving $O(N)$ complexity. GP regression is attractive in this context because the zero-mean prior directly encodes the physical expectation that displacements oscillate around a reference position, while the kernel hyperparameters control the expected displacement magnitude and correlation length. This acts as a principled regularization that prevents the low-frequency drift typical of numerical integration, without requiring manual selection of filter parameters. Furthermore, the state space formulation naturally accommodates multi-rate sensor fusion.

2 METHODOLOGY

The displacement $f(t)$ is modeled as a zero-mean GP with a Matérn 5/2 kernel (hyperparameters: length scale l_f, output std. σ_f), which is related to a state space model [4]: $\dot{\mathbf{x}}(t) = \mathbf{F}\mathbf{x}(t) + \mathbf{L}\mathbf{w}(t)$, with $f^{(n)}(t) = \mathbf{D}^{(n)}\mathbf{x}(t)$ extracting the n-th derivative. Noisy acceleration measurements enter as $\ddot{y}_k = \mathbf{D}^{(2)}\mathbf{x}_k + \varepsilon_k^{(a)}$, with $x_k = x(t_k)$ and $\varepsilon_k^{(a)} \sim \mathcal{N}(0, \sigma_a^2)$. Inference via the Kalman filter and RTS smoother yields the displacement estimate $\hat{f}_{k|N} = \mathbf{D}^{(0)}\hat{\mathbf{x}}_{k|N}$ with associated uncertainty. Hyperparameters are optimized by minimizing the negative log-likelihood with additional constraints on the output variance, as described in [3].

When low-rate displacement measurements are available, the measurement equation at those time steps is augmented as:

$$\begin{pmatrix} \ddot{y}_k \\ y_k^{(0)} \end{pmatrix} = \begin{pmatrix} \mathbf{D}^{(2)} \\ \mathbf{D}^{(0)} \end{pmatrix} \mathbf{x}_k + \begin{pmatrix} \varepsilon_k^{(a)} \\ \varepsilon_k^{(d)} \end{pmatrix}. \tag{1}$$

3 NUMERICAL EXAMPLE: 2D OFFSHORE WIND TURBINE UNDER WAVE AND WIND LOADING

The method is validated on a 2D finite element model of the NREL 5MW offshore wind turbine [5] supported on a monopile [6], modeled in OpenSees [7] and already employed in [3]. Acceleration measurements at the top of the turbine are assumed to be available with sampling frequency of 20 Hz and 5% noise. Two scenarios are considered with different significant wave height H_s, peak period T_p, and wind speed U to represent different loading conditions:

1. **Swell-dominated** ($H_s = 4$ m, $T_p = 12$ s, light wind, feathered blades): acceleration-only

estimation. The GP is compared with FFT integration and polynomial detrending.

2. **Combined wind and wave** (H_s = 2 m, T_p = 7 s, U = 12 m/s, parked blades): the low-frequency wind-induced response is not recoverable from acceleration alone, so additional displacement measurements at 1 Hz with 100% noise are fused. The GP is compared with the multi-rate Kalman filter of Smyth and Wu combined with the RTS smoother [2].

Swell refers to long-period ocean waves generated by distant storms. In the swell-dominated scenario, the structural response is primarily driven by wave loading, with negligible wind contribution. For the swell-dominated case (first scenario), the GP method successfully recovers the displacement from acceleration alone (see Figure 1). Under combined loading with parked blades (second scenario), the low-frequency wind-induced fluctuations degrade the performance the double integration from acceleration to displacement. The addition of low-frequency displacement measurements restores accurate estimation (Figure 2). Table 1 summarizes all results, comparing the GP with frequency-domain integration [1] at a fixed cutoff of 0.01 Hz, polynomial detrending, and the multi-rate Kalman filter and RTS smoother of Smyth and Wu [2]. The GP consistently achieves the highest coefficient of determination R^2 and lowest root mean square error (RMSE) — both computed excluding 30 s at both ends to avoid boundary effects especially for the FFT-integration.

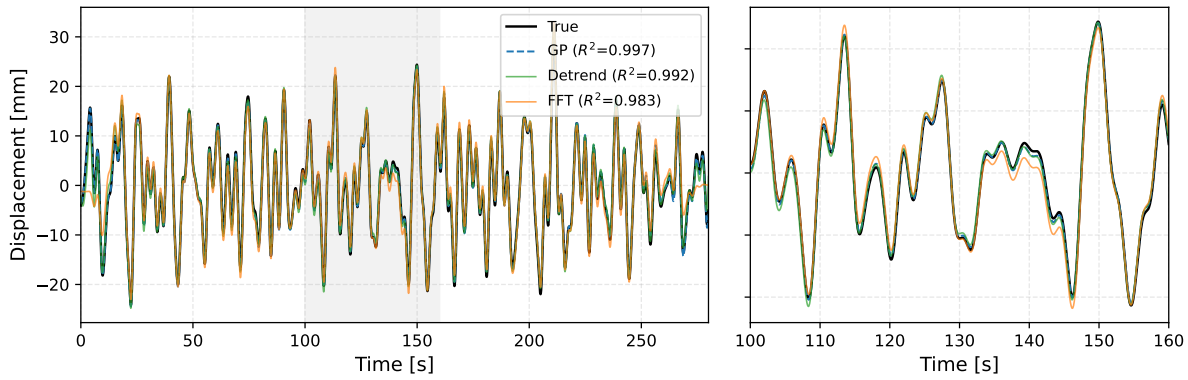


Figure 1: Displacement estimates for the swell-dominated case (significant effect of wave loading with minor wind influence, first scenario) using acceleration-only measurements: GP, FFT integration (0.01 Hz cutoff), and polynomial detrending.

Scenario	Method	RMSE [mm]	R^2
First scenario, acc. only	GP Matérn 5/2	0.5	0.997
	Poly. detrending	0.9	0.992
	FFT integration [1]	1.3	0.983
Second scenario, acc. + disp. fusion	GP Matérn 5/2	5.8	0.900
	Smyth & Wu [2]	6.7	0.863

Table 1: Summary of displacement estimation results across all scenarios.

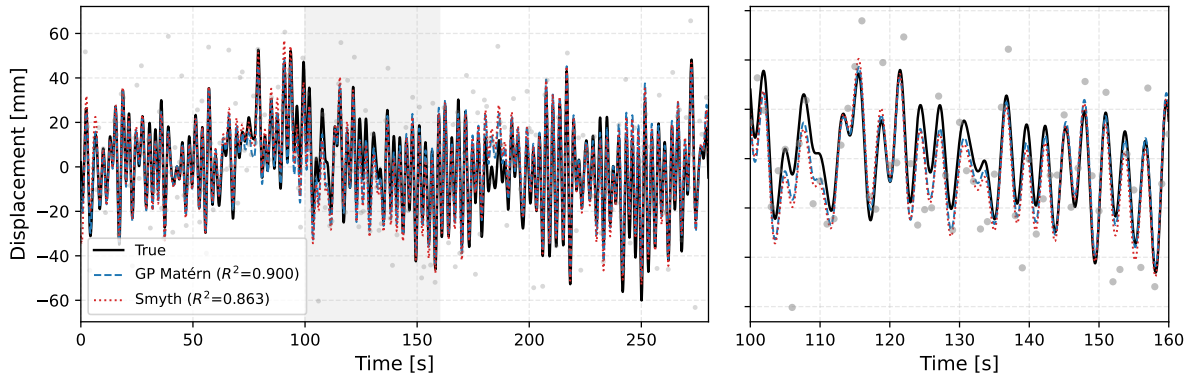


Figure 2: Acceleration and displacement fusion comparison: GP Matérn vs Smyth & Wu [2]. Acceleration at 20 Hz (5% noise), displacement at 1 Hz (100% noise). The grey dots represent noisy displacement measurements.

4 CONCLUSIONS

GP regression in state space form provides an effective approach for estimating displacements from accelerations, with uncertainty quantification, $O(N)$ complexity, and natural multi-rate sensor fusion. The method outperforms established integration techniques and multi-rate Kalman filtering on an numerically exemplified offshore wind turbine model under both swell-dominated and combined wind and wave loading. A key advantage over frequency-domain methods is that the GP does not require manual selection of a cutoff frequency, which can significantly affect the estimation quality. Instead, the kernel hyperparameters are optimized directly from the data via maximum likelihood with additional constraints. Future work includes the development of physics-informed kernels that encode structural dynamics knowledge into the GP prior.

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