

Revealing Transient Strain in Geodetic Data with the Radial Basis Function Finite Difference Method

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1 Introduction

Crustal strain rates are fundamentally important quantities for assessing seismic hazard, since knowing where and how quickly strain is accumulating gives insight into where we can expect stored elastic energy to be released seismically. It is then important to develop and improve upon methods for mapping strain in tectonically active regions because such maps could conceivably feed into seismic hazard models such as UCERF3 (Field et al., 2014).

Methods for estimating strain from geodetic data fall in one of two categories. There are model-based approaches which assume that strain is the result of loading on faults which have a known geometry, and there are data-based approaches which make no assumptions about the source of deformation. We will exclusively consider data-based approaches in this paper. The classic and simplest method for estimating strain is to assume that the strain rate is constant in time and spatially uniform within subnetworks of the geodetic data. Linear least squares is then used to find the components of the strain rate tensor for each subnetwork (e.g Frank, 1966; Prescott, 1976; Savage et al., 1986; Feigl et al., 1990; Murray and Lisowski, 2000). Several algorithms have been developed to improve upon this procedure. Shen et al. (1996) and Shen et al. (2015) discuss an algorithm where, instead of using the immediately adjacent stations to calculate strain at a position, the strain is computed with a weighted average over the entire network where the weighting is smaller for more distant stations. Another strategy is to fit a set of interpolating basis functions to the deformation field and then compute the strain from the analytical derivative of the interpolant (e.g. Beavan and Haines, 2001; Tape et al., 2009; Sandwell and Wessel, 2016).

The aforementioned studies have all been concerned with estimating long term strain rates. Time dependent strain would be useful for studying geophysical processes which occur over timescales of days to years such as slow slip events, postseismic relaxation, or volcanic deformation. Ohtani et al. (2010) identified transient strain events by fitting a set of spatial wavelet basis functions to the deformation field at discrete time epochs, and a Kalman filtering strategy was used to ensure that the coefficients for each basis function varied smoothly in time. Holt and Shcherbenko (2013) calculated time dependent strain by differentiating a bicubic interpolant that was fit to each epoch of a temporally smoothed deformation field.

Each of the methods described above are designed to overcome two complications that arise in estimating deformation gradients: (1) geodetic data are noisy and differentiation will only amplify the noise and (2) geodetic data are not observed on a regular grid, which prevents the use of standard finite difference methods for computing derivatives. In this paper we demonstrate that both of these complications can be elegantly handled with the Radial Basis Function-Finite Difference (RBF-FD) method.

The RBF-FD method was developed simultaneously and independently by Tolstykh and Shirobokov (2003), Shu et al. (2003), Cecil et al. (2004), and Wright and Fornberg (2006) as a computationally efficient way to solve large scale partial differential equations over irregular, multi-dimensional domains. The RBF-FD method can be thought of as a generalization of the traditional finite difference method, where the node layout is no longer restricted to regular grids. Indeed, the RBF-FD method can be used to estimate derivatives of discrete data located at arbitrary scattered positions in multi-dimensional space. The RBF-FD method is particularly appealing because it is algorithmically simple, regardless of the domain shape or node layout, and also because the method has performed well in numerous benchmark tests (?, and references therein).

In this paper, we do not use the RBF-FD method to solve a partial differential equation, but rather we use it to spatially smooth geodetic data and to compute deformation gradients. Our smoothing strategy can be viewed as a non-parametric, low-pass filter for scattered data where the degree of smoothness is controlled by a user specifies cutoff frequency. This can be contrasted with interpolation based methods where the resulting interpolant can be largely and perhaps unpredictably controlled by the choice of basis function. This process of smoothing and differentiating can be extended to estimate time dependent strain rates. In that case, we first temporally smooth and differentiate GPS displacement time series to get time dependent velocities. We

then spatially smooth and differentiate the resulting velocities for each time epoch to get time dependent strain rates.

The method proposed in this paper has numerous advantages which set it apart from other methods for computing strain rates. The method is computationally efficient and stable (there is no inversion of an ill-conditioned matrix). There are no hyper parameters or penalty parameters that need to be tuned for each application. As opposed to interpolation strategies such as Beavan and Haines (2001), Tape et al. (2009), or Ohtani et al. (2010), our method assumes that velocities are locally rather than globally continuous, which allows us to easily handle discontinuities resulting from, for example, a creeping fault.

We begin this paper by summarizing the RBF-FD scheme and explaining how we construct differentiation matrices for scattered data. We then introduce the RBF-FD filter, which is used to smooth the observed geodetic data prior to differentiation. We provide two real world demonstrations of our method for calculating strain rates. First we calculate the long term strain rates in Southern California from the CMM3 velocity data set (Shen et al., 2011), and we verify that our results are consistent with other studies. We then calculate time dependent strain rates in Cascadia from the GPS data provided by UNAVCO. In Cascadia, we analyze strain resulting from slow slip events and compare it to the long term tectonic strain accumulation. Slow slip events are found to produce compression in the Olympic Peninsula, which is in addition to the compression resulting from tectonic loading. Further south in Oregon, the slow slip events tend to release the compressional strain that is accumulated tectonically. While similar conclusions have been drawn from fault slip inversions for slow slip events, it is important to recognize that slip inversion are the product of inverting an ill-conditioned matrix making it difficult to determine whether slip inferences are real or just an artifact of the inversion. The strain rates presented in this paper are more direct observations and can be interpreted with a higher degree of confidence.

2 Method

In this section, we describe how GNSS displacement observations are used to identify transient crustal strain rates, which we denote as $\dot{\epsilon}(z)$, where z is the ordered pair (x, t) , x are spatial coordinates in \mathbb{R}^2 , and t is time. We consider $\dot{\epsilon}$ to be spatially and temporally coherent deviations from the steady rate of strain accumulation from plate tectonics. We determine $\dot{\epsilon}$ by first identifying transient displacements, $\mathbf{u}(z)$, which we then spatially and temporally differentiate. As we will show in Section X, estimates of $\dot{\epsilon}$ turn out to be more effective at illuminating geophysical signal than estimates of \mathbf{u} or $\dot{\mathbf{u}}$. We make a prior assumption that each component of \mathbf{u} is a Gaussian process,

$$u_i(z) \sim \mathcal{N}(0, C_{u_i}), \quad (1)$$

where $C_{u_i}(z, z')$ is a covariance function indicating how we expect $u_i(z)$ to covary with $u_i(z')$. For simplicity, we treat each component of displacement independently and ignore any potential covariance. We then drop the component subscripts with the understanding that the same analysis is being repeated to estimate the east, north, and vertical components of \mathbf{u} . We further assume that C_u can be separated into positive definite spatial and temporal functions as

$$C_u((x, t), (x', t')) = X(x, x')T(t, t'). \quad (2)$$

The appropriate choice for X and T may vary depending on the geophysical signal we are trying to describe (e.g. postseismic deformation or deformation from slow slip events), and we discuss this matter in the next section.

We constrain u with GNSS data, which records u as well as other physical and non-physical processes which we are not interested in. We describe GNSS observations at position x_i and time t as a realization of the random variable

$$d_i(t) = u(x_i, t) + \epsilon(x_i, t) + a_i + b_i t + c_i \sin(2\pi t) + q_i \cos(2\pi t) + r_i \sin(4\pi t) + s_i \cos(4\pi t), \quad (3)$$

where a_i is an offset that is unique for each GNSS monument, b_i is the steady rate of tectonic deformation at x_i , the sinusoids describe seasonal deformation (using units of years for t), and ϵ is a Gaussian process for noise that cannot be described parametrically. For example, ϵ can consist of white noise, temporally correlated noise describing benchmark wobble (e.g., Wyatt, 1982, 1989), and/or spatially correlated noise describing common mode error (e.g., Wdowinski et al., 1997). For now, ϵ will simply be described as $\epsilon \sim \mathcal{N}(0, C_\epsilon)$. We consider the six coefficients in eq. (3) to be uncorrelated random variables distributed as $\mathcal{N}(0, \lambda^2)$ in the limit as $\lambda \rightarrow \infty$ (i.e., the coefficients have diffuse priors). Of course, the tectonic deformation, b_i , is spatially correlated and we could invoke a tectonic model to form a prior on b_i . However, in our application to Cascadia, we will be using displacement time series which are long enough to sufficiently constrain b_i for each station, and there is no need to incorporate a prior. Likewise, the seasonal coefficients may be spatially correlated (Langbein, 2008), and it may be worth exploring and exploiting such a correlation in a future study.

We now consider the column vector of n GNSS observations, \mathbf{d}_* . Let \mathbf{y} be the set of (x_i, t) pairs describing where and when each of the GNSS observations have been made. Furthermore, let \mathbf{a} be the vector of coefficients from eq. (3) for each of the m GNSS monuments, and let \mathbf{P} be the $n \times 6m$ matrix of corresponding basis functions evaluated at each point in \mathbf{y} . The observations \mathbf{d}_* are then a realization of the random vector

$$\mathbf{d} = u(\mathbf{y}) + \epsilon(\mathbf{y}) + \mathbf{P}\mathbf{a}, \quad (4)$$

which is distributed as $\mathcal{N}(\mathbf{0}, \mathbf{C}_d)$, where

$$\mathbf{C}_d = C_u(\mathbf{y}, \mathbf{y}) + C_\epsilon(\mathbf{y}, \mathbf{y}) + \lambda^2 \mathbf{P}\mathbf{P}^T. \quad (5)$$

It should be understood that the notation $f(\mathbf{x})$ and $f(\mathbf{x}, \mathbf{y})$ is shorthand for $[f(x_i)]_{x_i \in \mathbf{x}}$ and $[f(x_i, y_j)]_{(x_i, y_j) \in \mathbf{x} \times \mathbf{y}}$, respectively.

We now describe how to condition the prior for each component of transient displacements, u , with \mathbf{d}_* to form a posterior estimate of transient displacements, $\hat{u} = u|\mathbf{d}_*$. We will assume that an appropriate covariance functions and corresponding hyperparameters for X , T , and C_ϵ have already been chosen. If λ is kept finite, then we can follow Rasmussen and Williams (2006) to find that \hat{u} is distributed as $\mathcal{N}(\mu_{\hat{u}}, C_{\hat{u}})$, where

$$\mu_{\hat{u}}(z) = C_u(z, \mathbf{y}) \mathbf{C}_d^{-1} \mathbf{d}_* \quad (6)$$

and

$$C_{\hat{u}}(z, z') = C_u(z, \mathbf{y}) \mathbf{C}_d^{-1} C_u(\mathbf{y}, z'). \quad (7)$$

However, we are interested in the limit as $\lambda \rightarrow \infty$, and the form for eq. (6) and eq. (7) is not suitable for evaluating this limit. We can use the partitioned matrix inversion identity (e.g., Press et al., 2007) to rewrite eq. (6) and eq. (7) as

$$\mu_{\hat{u}}(z) = \begin{bmatrix} C_u(z, \mathbf{y}) & \mathbf{0} \end{bmatrix} \begin{bmatrix} C_u(\mathbf{y}, \mathbf{y}) + C_\epsilon(\mathbf{y}, \mathbf{y}) & \mathbf{P} \\ \mathbf{P}^T & -\lambda^{-2} \mathbf{I} \end{bmatrix}^{-1} \begin{bmatrix} \mathbf{d}_* \\ \mathbf{0} \end{bmatrix} \quad (8)$$

and

$$C_{\hat{u}}(z, z') = C_u(z, z') - \begin{bmatrix} C_u(z, \mathbf{y}) & \mathbf{0} \end{bmatrix} \begin{bmatrix} C_u(\mathbf{y}, \mathbf{y}) + C_\epsilon(\mathbf{y}, \mathbf{y}) & \mathbf{P} \\ \mathbf{P}^T & -\lambda^{-2} \mathbf{I} \end{bmatrix}^{-1} \begin{bmatrix} C_u(\mathbf{y}, z') \\ \mathbf{0} \end{bmatrix}. \quad (9)$$

Taking the limit as $\lambda \rightarrow \infty$, we get the solution for the mean and covariance of \hat{u} ,

$$\mu_{\hat{u}}(z) = \begin{bmatrix} C_u(z, \mathbf{y}) & \mathbf{0} \end{bmatrix} \begin{bmatrix} C_u(\mathbf{y}, \mathbf{y}) + C_\epsilon(\mathbf{y}, \mathbf{y}) & \mathbf{P} \\ \mathbf{P}^T & \mathbf{0} \end{bmatrix}^{-1} \begin{bmatrix} \mathbf{d}_* \\ \mathbf{0} \end{bmatrix} \quad (10)$$

and

$$C_{\hat{u}}(z, z') = C_u(z, z') - \begin{bmatrix} C_u(z, \mathbf{y}) & \mathbf{0} \end{bmatrix} \begin{bmatrix} C_u(\mathbf{y}, \mathbf{y}) + C_\epsilon(\mathbf{y}, \mathbf{y}) & \mathbf{P} \\ \mathbf{P}^T & \mathbf{0} \end{bmatrix}^{-1} \begin{bmatrix} C_u(\mathbf{y}, z') \\ \mathbf{0} \end{bmatrix}. \quad (11)$$

The posterior transients displacements, $\hat{\mathbf{u}}$, are found by evaluating eq. (10) and (11) for each displacement component. We differentiate the Gaussian process $\hat{\mathbf{u}}$ (see Abrahamsen (1997)) to form an estimate of transient strain rate, $\dot{\epsilon}$, which is itself a spatially and temporally continuous Gaussian process. The components of the transient strain rate tensor, $\dot{\epsilon}_{ij}$, are given by

$$\dot{\epsilon}_{ij}(z) = \frac{1}{2} \frac{\partial}{\partial t} \left(\frac{\partial \hat{u}_i(z)}{\partial x_j} + \frac{\partial \hat{u}_j(z)}{\partial x_i} \right). \quad (12)$$

which are distributed as $\mathcal{N}(\mu_{\dot{\epsilon}_{ij}}, C_{\dot{\epsilon}_{ij}})$, where

$$\mu_{\dot{\epsilon}_{ij}}(z) = \frac{1}{2} \frac{\partial}{\partial t} \left(\frac{\partial \mu_{\hat{u}_i}(z)}{\partial x_j} + \frac{\partial \mu_{\hat{u}_j}(z)}{\partial x_i} \right) \quad (13)$$

and

$$C_{\dot{\epsilon}_{ij}}(z, z') = \frac{1}{4} \frac{\partial^2}{\partial t \partial t'} \left(\frac{\partial^2 C_{\hat{u}_i}(z, z')}{\partial x_j \partial x'_j} + \frac{\partial^2 C_{\hat{u}_j}(z, z')}{\partial x_i \partial x'_i} \right). \quad (14)$$

2.1 Outlier detection

In our formulation for estimating transient strain rates, we have assumed that noise in the data vector is normally distributed. This is not an appropriate assumption for GNSS displacement timeseries which are prone to more outliers than would be predicted for normally distributed noise. It follows that proposed methods for analyzing GNSS timeseries should be robust against outliers (e.g., Blewitt et al., 2016). In order to make our estimates of transient strain more robust, we automatically identify and remove outliers in the GNSS data as a pre-processing step.

Our method for detecting outliers is based on the data editing algorithm described in Gibbs (2011). We again treat \mathbf{d}_* as a sample of \mathbf{d} , and we assume some prior covariance function for u . The choice for u here does not need to be the same as that used in Section X, and a conservative approach would be to choose a u that is more flexible (e.g., shorter characteristic length-scales and higher variance). We let ϵ be uncorrelated noise which has standard deviation given by the formal data uncertainties, $\boldsymbol{\sigma}$. We consider outliers to be observations which are abnormally inconsistent with the random vector $u(\mathbf{y}) + \mathbf{P}\mathbf{a}$. With this criterion, we take into account the spatial and temporal relationship between the data, allowing us to identify anomalous observations which may not be immediately apparent based on inspection of individual timeseries. To begin the algorithm, we let Ω be the index set of non-outliers in \mathbf{d}_* and initiate it with all n indices. This algorithm is iterative, and for each iteration we calculate the residual vector

$$\mathbf{r} = \frac{\mathbf{d}_* - \mathbb{E}[(u(\mathbf{y}) + \mathbf{P}\mathbf{a})|\tilde{\mathbf{d}}_*]}{\boldsymbol{\sigma}} \quad (15)$$

$$= \frac{1}{\boldsymbol{\sigma}} \left(\mathbf{d}_* - \begin{bmatrix} C_u(\mathbf{y}, \tilde{\mathbf{y}}) & \mathbf{P} \end{bmatrix} \begin{bmatrix} C_u(\tilde{\mathbf{y}}, \tilde{\mathbf{y}}) + \text{diag}(\tilde{\boldsymbol{\sigma}}^2) & \tilde{\mathbf{P}} \\ \tilde{\mathbf{P}}^T & \mathbf{0} \end{bmatrix}^{-1} \begin{bmatrix} \tilde{\mathbf{d}}_* \\ \mathbf{0} \end{bmatrix} \right), \quad (16)$$

where the tilde indicates that only elements corresponding to indices in Ω are retained (e.g., $\tilde{\mathbf{y}} = (\mathbf{y}_i)_{i \in \Omega}$). We then update Ω to be

$$\Omega = \{i : |\mathbf{r}_i| < \eta \tilde{\mathbf{r}}_{rms}\} \quad (17)$$

where $\tilde{\mathbf{r}}_{rms}$ is the root-mean-square of $\tilde{\mathbf{r}}$ and λ is an outlier tolerance. We use $\lambda = 4$ in this study, which seems to accurately identify outliers without unnecessarily decimating the data. Iterations continue until the new Ω is equal to the previous Ω (i.e., no new outliers are detected).

It should be noted that this algorithm does not identify jumps in GNSS time series, which are another common defect. Some, but not all, jumps can be automatically removed by parsing station logs and identifying dates of antenna changes. However, it is still necessary to manually inspect and remove jumps of unknown origin. That being said, this outlier detection algorithm significantly reduces the effort needed to manually clean GNSS data.

2.2 Spatial and temporal covariance functions

We must choose an appropriate Gaussian process describing transient displacements u and GNSS noise ϵ . We assume that u and ϵ both have zero mean, which leaves for use to select a parameterization for the covariance functions X , T , and C_d . In this section, we list the covariance functions which are considered in this paper and those which could be of use in future studies. In the following discussion α and β are hyperparameters. There are numerous strategies for selecting these hyperparameters (see Cressie (1993)) and we save a discussion on choosing the hyperparameters for Section X.

The squared exponential covariance function,

$$C(x, x') = \alpha^2 \exp\left(\frac{-\|x - x'\|_2^2}{2\beta^2}\right), \quad (18)$$

is commonly used in Kriging (e.g., Cressie, 1993) and Gaussian process regression (e.g., Rasmussen and Williams, 2006). The squared exponential is a valid (i.e. positive definite) covariance function for any number of spatial dimensions, and it describes an isotropic (i.e. $C(x, x')$ can be expressed as $\hat{C}(\|x - x'\|_2)$) Gaussian processes with realizations that are infinitely differentiable. Kato et al. (1998) and El-Fiky and Kato (1999) demonstrated that eq. (18) is an appropriate covariance model for describing long-term tectonic strain rates for Japan.

The Wendland class of covariance functions (Wendland, 2005) are positive definite in \mathbb{R}^d , and they describes an isotropic Gaussian process with realizations that can be differentiated k times. The form of the covariance function depends on the choice of d and k . Wendland covariance functions have compact support, which is a particularly useful property because we can exploit the sparsity of the the corresponding covariance matrices. In this study we use Wendland covariance functions to describe the temporal component of transient displacements. Therefore, we only require that $d = 1$ and $k = 1$. The corresponding Wendland covariance function is

$$C(x, x') = \alpha^2 \left(1 - \frac{|x - x'|}{\beta}\right)_+^3 \left(\frac{3|x - x'|}{\beta} + 1\right), \quad x, x' \in \mathbb{R}^1, \quad (19)$$

where

$$(x)_+ = \begin{cases} x, & x > 0 \\ 0, & \text{otherwise.} \end{cases} \quad (20)$$

We next consider the covariance function which describes a first-order Gauss-Markov (FOGM) process. A FOGM process is a solution to the stochastic differential equation

$$\dot{u}(x) + \alpha u(x) = \beta w(x), \quad x, x' \in \mathbb{R}^1, \quad (21)$$

where $w(x)$ is white noise with unit variance. The solution is a Gaussian process with zero mean and covariance

$$C(x, x') = \frac{\beta^2}{2\alpha} \exp(-\alpha|x - x'|), \quad x, x' \in \mathbb{R}^1. \quad (22)$$

FOGM processes are isotropic and realizations are not differentiable. The FOGM model has been used to describe temporally correlated noise in EDM data (Langbein, 2004) and GNSS data (e.g., Langbein, 2008).

One last covariance function which is worth mentioning, even though we do not use it in this paper, is the periodic covariance function (Mackay, 1998),

$$C(x, x') = \alpha^2 \exp\left(\frac{-\sin(\frac{\pi}{\lambda}|x - x'|)^2}{2\beta^2}\right), \quad x, x' \in \mathbb{R}^1. \quad (23)$$

The periodic covariance function describes an isotropic Gaussian process with realizations that have period λ . The length-scale of features within each period is controlled by β . In terms of GNSS data, a periodic Gaussian process can be used to describe seasonal deformation. The more common method of treating seasonal deformation is to model it as a linear combination of annual and semi-annual sinusoids (e.g., Dong et al., 2002). We believe there is potential to use periodic Gaussian processes to explore the statistical properties of seasonal signals; however, that is outside the scope of this paper.

Brownian motion and integrated Brownian motion are two Gaussian processes which are frequently used in the geodetic literature. Brownian motion, which has zero mean and covariance function

$$C(x, x') = \alpha^2 \min(x, x'), \quad x, x' \in \mathbb{R}^1 \text{ and } x, x' \geq 0, \quad (24)$$

is commonly used to describe noise resulting from the instability of geodetic monuments (e.g., Wyatt, 1982, 1989; Langbein and Johnson, 1997). Integrated Brownian motion, which has zero mean and covariance function

$$C(x, x') = \int_0^x \int_0^{x'} \alpha^2 \min(u, u') du' du \quad (25)$$

$$= \frac{\alpha^2}{2} \min(x, x')^2 \left(\max(x, x') - \frac{1}{3} \min(x, x') \right), \quad x, x' \in \mathbb{R}^1 \text{ and } x, x' \geq 0, \quad (26)$$

has been used as a nonparametric model for the time dependence of geophysical signals (e.g., Segall and Mathews, 1997; McGuire and Segall, 2003; Ohtani et al., 2010; Hines and Hetland, 2016). It should be noted that Brownian motion and integrated Brownian motion have a reference time at which the Gaussian process is exactly zero. For some geophysical signals, such as postseismic deformation, it is reasonable to have such a reference time. On the other hand, if there is no sense of a start time for the geophysical process, then Brownian motion or integrated Brownian motion may not be appropriate, and one of the isotropic Gaussian processes described above should be used.

3 Application Cascadia Slow Slip Events

We demonstrate the method for estimating transient strain described in the previous section by applying it to GNSS data in Cascadia. We are mainly interested in identifying transient strain resulting from slow slip events (SSEs) (e.g., Dragert et al., 2001). We show that Gaussian processes are an effective tool for (1) detecting SSEs and (2) understanding how the strain from SSEs are contributing to the strain accumulated over the seismic cycle. Our primary motivation for detecting SSEs is because there have been several documented cases of SSEs triggering megathrust earthquakes (Roeloffs, 2006). In Cascadia, there is less of a need to detect SSEs with GNSS data because the SSEs are associated with a spike in seismic tremor, which is actively monitored by the Pacific Northwest Seismic Network (PNSN) (Wech, 2010). However, SSEs have been observed in other subduction zones without any associated tremor (Schwartz and Rokosky, 2007), and so there is still utility in developing method for detecting SSEs with GNSS data. Furthermore, by comparing our estimated transient strain in Cascadia with the tremor catalog, we can verify the accuracy of method for detecting SSEs.

3.1 Noise model

In this section we discuss our choice for the noise covariance function C_ϵ . We will assume that the noise consists of uncorrelated noise with standard deviation given by the formal data uncertainties and potentially spatially and/or temporally correlated noise. There have been numerous studies on temporally correlated noise in GNSS data (Zhang et al., 1997; Mao et al., 1999; Williams et al., 2004; Langbein, 2008, e.g.). These studies have found some combination of Brownian motion or flicker noise best describes the temporally correlated noise in GNSS data. Brownian motion has also been used to describe error resulting from an unstable geodetic monument (e.g., Wyatt, 1982, 1989). We assume that temporally correlated noise can be described by a FOGM stochastic model, noting that the Brownian motion is a degenerate case of a FOGM process.

To determine the appropriate hyperparameters for the FOGM model, α and β , we first select 38 stations in Washington and Oregon which are east of 121° W, where we can reasonably expect no transient signal from SSEs (i.e. $u = 0$). We then find α and β for each station timeseries with the Restricted Maximum Likelihood (REML) method (e.g., Harville, 1974; Cressie, 1993) and Hines 2017. The REML method finds the hyperparameters which maximize the probability of drawing \mathbf{d}_* from \mathbf{d} . We use the REML method over the maximum likelihood (ML) method (e.g., Langbein and Johnson, 1997) because the REML method properly accounts for the improper prior that we assigned to \mathbf{a} . The distribution of inferred α and β are shown in Figure X. The amplitude of FOGM noise for the east and north components is notably low and are unimodally clustered around $0.5 \text{ mm/yr}^{0.5}$. The corresponding estimates of α tend to cluster around 0 yr^{-1} , which is the degenerate case where FOGM behaves like Brownian motion. The amplitude of FOGM noise for the vertical component is significantly larger with a median value of $13.8 \text{ mm/yr}^{0.5}$. The inferred values for α are higher for the vertical component with a median value of 1.87 yr^{-1} . In Figure X, we use the median values of α and β to generate two random samples of FOGM noise. The samples span seven years and over these seven years the east and north samples drift by about 1 mm. In the context of detecting SSEs, which produce several mm's of surface displacement on the timescale of weeks to months, the estimated FOGM noise for the east and north component is negligible. In contrast, the estimated FOGM noise for the vertical component is significantly larger than the signal we would expect from SSEs. We suspect that the higher amplitude for the FOGM model in the vertical component is accommodating for deficiencies in our rather simple seasonal model. Based on this analysis, we henceforth ignore temporally correlated noise in the east and north component because of its low amplitude, and we do not estimate u for vertical deformation because of the low signal to noise ratio.

Another significant source of noise in GNSS data is common mode error (e.g., Wdowinski et al., 1997), which is noise that is highly spatially correlated. When not accounted for, common mode error manifests itself as spatially uniform undulations in \hat{u} . However, we are primarily interested in estimating strain which is insensitive to common mode error. We therefore do not include common mode error in our noise model.

Our noise is just white.

3.2 Transient displacement model

model exhibits the same relationship which can be described

Both of which have clear implications for assessing seismic hazard.

, which can have applications for seismic hazard assessment. Identifying strain resulting from ETS events serves two purposes: (1) ETS events have events which were first discovered by Dragert et al. (2001).

We demonstrate that Gaussian processes are effective tools for detecting transient strain by using them to detect Cascadia slow slip events.

BACKGROUND

Dragert et al. (2001) first discovered slow slip events

Explain strain concentration with this: Slow slip event depths from Dragert et al. (2001), Wech et al. (2009), Schmidt and Gao (2010), Bartlow et al. (2011) show slip concentrated at depths from 30 to 50 km depth.

Interseismic locking depths from Flück et al. (1997), Murray and Lisowski (2000), McCaffrey et al. (2007) and McCaffrey et al. (2013), Burgette et al. (2009), Schmalzle et al. (2014) are consistent with a full locking down to about 20 km.

Studies which simultaneously modeled interseismic and ets are Holtkamp and Brudzinski (2010) and Schmalzle et al. (2014)

4 Discussion and Conclusion

The material presented in this paper is primarily focused on GPS data; however, we speculate that the RBF-FD scheme can be of particular use in denoising borehole strain meter (BSM) data. The Plate Boundary Observatory has deployed X BSMs along the Western United States. BSM data contains low frequency drift resulting from relaxation of the borehole (Gladwin et al., 1987), which can obscure the geophysical signal of interest. We suggest that the RBF-FD scheme may be useful in denoising BSM data. Since the RBF-FD scheme

provides a straight-forward mapping from GPS displacements to strain at any target locations, it is possible to use GPS derived strains as *a priori* information for strain at BSM sites. GPS derived strains could then aid in discerning tectonic signal from noise in BSM data.

Additional uses for strain: transient detection, prior for strain meters,

Additional potential applications of the RBF-FD method: regularizing inverse problems,

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