

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

Trever T. Hines and Eric A. Hetland

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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 (Fornberg and Flyer, 2015, 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. ϵ can consist of white noise, temporally correlated noise describing, for example, benchmark wobble (e.g., Wyatt, 1982, 1989), and/or spatially correlated noise describing, for example, common mode error (e.g., Wdowinski et al., 1997). For now, we describe ϵ generally 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 in reality spatially correlated and we could invoke 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 as suggested by Langbein2008?. It may be worth exploring and exploiting such a correlation in a future study.

Let \mathbf{y} be the set of (x_i, t) pairs describing where and when each of the n 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 n GNSS observations, \mathbf{d}_* , are 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 used as 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. In section X, we describe how the observations \mathbf{d}_* are used to constrain transient displacements u and then for estimates of transient strain rates.

2.1 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,

$$C(x, x') = \alpha^2 \exp\left(\frac{-\|x - x'\|_2^2}{2\beta^2}\right), \quad (6)$$

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. (6) 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

$$C(x, x') = \alpha^2 \left(1 - \frac{|x - x'|}{\beta}\right)_+^3 \left(\frac{3|x - x'|}{\beta} + 1\right), \quad x, x' \in \mathbb{R}^1, \quad (7)$$

where

$$(x)_+ = \begin{cases} x, & x > 0 \\ 0, & \text{otherwise.} \end{cases} \quad (8)$$

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

$$\dot{u}(x) + \alpha u(x) = \beta w(x), \quad x, x' \in \mathbb{R}^1, \quad (9)$$

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

$$C(x, x') = \frac{\beta^2}{2\alpha} \exp(-\alpha|x - x'|), \quad x, x' \in \mathbb{R}^1. \quad (10)$$

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),

$$C(x, x') = \alpha^2 \exp\left(\frac{-\sin(\frac{\pi}{\lambda}|x - x'|)^2}{2\beta^2}\right), \quad x, x' \in \mathbb{R}^1. \quad (11)$$

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

$$C(x, x') = \alpha^2 \min(x, x'), \quad x, x' \in \mathbb{R}^1 \text{ and } x, x' \geq 0, \quad (12)$$

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

$$C(x, x') = \int_0^x \int_0^{x'} \alpha^2 \min(u, u') du' du \quad (13)$$

$$= \frac{\alpha^2}{2} \min(x, x')^2 \left(\max(x, x') - \frac{1}{3} \min(x, x') \right), \quad x, x' \in \mathbb{R}^1 \text{ and } x, x' \geq 0, \quad (14)$$

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.

2.2 Conditioning

In this section we describe how to condition the prior for transient displacements, u , with GNSS observations, \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

$$\mu_{\hat{u}}(z) = C_u(z, \mathbf{y}) C_{\mathbf{d}}^{-1} \mathbf{d}_* \quad (15)$$

and

$$C_{\hat{u}}(z, z') = C_u(z, \mathbf{y}) C_{\mathbf{d}}^{-1} C_u(\mathbf{y}, z'). \quad (16)$$

However, we are interested in the limit as $\lambda \rightarrow \infty$, and the form for eq. (15) and eq. (16) is not suitable for evaluating this limit. We can use the partitioned matrix inversion identity (e.g., Press et al., 2007) to rewrite eq. (15) and eq. (16) as

$$\mu_{\hat{u}}(z) = \begin{bmatrix} C_u(z, \mathbf{y}) & \mathbf{0} \end{bmatrix} \begin{bmatrix} C_u(\mathbf{y}, \mathbf{y}) + C_\epsilon(\mathbf{y}, \mathbf{y}) & \mathbf{P} \\ \mathbf{P}^T & -\lambda^{-2} \mathbf{I} \end{bmatrix}^{-1} \begin{bmatrix} \mathbf{d}_* \\ \mathbf{0} \end{bmatrix} \quad (17)$$

and

$$C_{\hat{u}}(z, z') = C_u(z, z') - \begin{bmatrix} C_u(z, \mathbf{y}) & \mathbf{0} \end{bmatrix} \begin{bmatrix} C_u(\mathbf{y}, \mathbf{y}) + C_\epsilon(\mathbf{y}, \mathbf{y}) & \mathbf{P} \\ \mathbf{P}^T & -\lambda^{-2} \mathbf{I} \end{bmatrix}^{-1} \begin{bmatrix} C_u(\mathbf{y}, z') \\ \mathbf{0} \end{bmatrix}. \quad (18)$$

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

$$\mu_{\hat{u}}(z) = \begin{bmatrix} C_u(z, \mathbf{y}) & \mathbf{0} \end{bmatrix} \begin{bmatrix} C_u(\mathbf{y}, \mathbf{y}) + C_\epsilon(\mathbf{y}, \mathbf{y}) & \mathbf{P} \\ \mathbf{P}^T & \mathbf{0} \end{bmatrix}^{-1} \begin{bmatrix} \mathbf{d}_* \\ \mathbf{0} \end{bmatrix} \quad (19)$$

and

$$C_{\hat{u}}(z, z') = C_u(z, z') - \begin{bmatrix} C_u(z, \mathbf{y}) & \mathbf{0} \end{bmatrix} \begin{bmatrix} C_u(\mathbf{y}, \mathbf{y}) + C_\epsilon(\mathbf{y}, \mathbf{y}) & \mathbf{P} \\ \mathbf{P}^T & \mathbf{0} \end{bmatrix}^{-1} \begin{bmatrix} C_u(\mathbf{y}, z') \\ \mathbf{0} \end{bmatrix}. \quad (20)$$

which allows us to evaluate the limit and we consider the GNSS observations \mathbf{d}_* to be a realization of \mathbf{d} . Furthermore, The random vector \mathbf{d} is distributed as $\mathbf{d} \sim \mathcal{N}(\bar{\mathbf{d}}, C_{\mathbf{d}})$, where

$$\mathbf{d} \quad (21)$$

We consider the column vector of GNSS observations, \mathbf{d}_* , to be realizations of d_{ij} at the positions and times in \mathbf{y} (i.e., $\mathbf{d}_* = [d_{ij}(\omega_*)]_{(x_i, t_j) \in \mathbf{y}}^T$). We want to find the posterior estimate of transient displacements, $u|\mathbf{d}_*$, which incorporates our prior and the GNSS observations.

Once we have chosen covariance functions and corresponding hyperparameters for X , T , and C_d , we then condition our prior Gaussian process, u , with the observations \mathbf{d}_* to form a posterior estimate of transient displacements, $u|\mathbf{d}_*$. \mathbf{d}_* is a realization of the

Whichever the Gaussian processes describing transient displacements, u , and noise in the GNSS data, ϵ , have covariance functions which

Optimal Hyperparameters

Conditioning the GP

Differentiation, scaling and addition to get strain

2.3 Time Dependent Strain Rate in Cascadia

BACKGROUND

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

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)

METHOD

We use GPS displacement time series to make daily estimates of strain rates from 2010-01-01 to 2016-07-01 in the Pacific Northwest. Our method consists of two distinct steps; we temporally smooth and differentiate the displacement time series for each station, and then we spatially smooth and differentiate the velocity field for each day. We temporally smooth the GPS displacements with the method described in ??, and we treat days with missing data as observations with infinite uncertainty. As noted above, this is effectively equivalent to fitting a smoothing spline to each time series, which can also be efficiently done with a Kalman filtering strategy (Kohn and Ansley, 1987). We chose a cutoff frequency of ZZZ, which is high enough to accurately describe deformation during a slow slip event. Spatial smoothing is done with the RBF-FD filter and differentiation to get the strain rates was done with the RBF-FD scheme. We picked a cutoff frequency of XXX for smoothing.

3 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,

References

- Bartlow, N. M., Miyazaki, S., Bradley, A. M., and Segall, P. (2011). Spacetime correlation of slip and tremor during the 2009 Cascadia slow slip event. 38(L18309):1–6.
- Beavan, J. and Haines, J. (2001). Contemporary horizontal velocity and strain rate fields of the Pacific-Australian plate boundary zone through New Zealand. *Journal of Geophysical Research*, 106(B1):741–770.
- Burgette, R. J., Weldon, R. J., and Schmidt, D. A. (2009). Interseismic uplift rates for western Oregon and along-strike variation in locking on the Cascadia subduction zone. *Journal of Geophysical Research: Solid Earth*, 114(1):1–24.
- Cecil, T., Qian, J., and Osher, S. (2004). Numerical methods for high dimensional Hamilton-Jacobi equations using radial basis functions. *Journal of Computational Physics*, 196(1):327–347.

- Cressie, N. (1993). *Statistics for Spatial Data*. John Wiley & Sons, New York, rev. edition.
- Dong, D., Fang, P., Bock, Y., Cheng, M. K., and Miyazaki, S. (2002). Anatomy of apparent seasonal variations from GPS-derived site position time series. *J. Geophys. Res.*, 107(B4):2075.
- Dragert, G., Wang, K., and James, T. S. (2001). A silent slip event on the deeper Cascadia subduction interface. *Science*, 292:1525–1528.
- El-Fiky, G. S. and Kato, T. (1999). Continuous distribution of the horizontal strain in the Tohoku district, Japan, predicted by least-squares collocation. *Journal of Geodynamics*, 27(2):213–236.
- Feigl, K. L., King, R. W., and Jordan, T. H. (1990). Geodetic measurement of tectonic deformation in the Santa Maria Fold and Thrust Belt, California. *Journal of Geophysical Research: Solid Earth*, 95(B3):2679–2699.
- Field, E. H., Arrowsmith, R. J., Biasi, G. P., Bird, P., Dawson, T. E., Felzer, K. R., Jackson, D. D., Johnson, K. M., Jordan, T. H., Madden, C., Michael, A. J., Milner, K. R., Page, M. T., Parsons, T., Powers, P. M., Shaw, B. E., Thatcher, W. R., Weldon, R. J., and Zeng, Y. (2014). Uniform California Earthquake Rupture Forecast, version 3 (UCERF3) -The time-independent model. *Bulletin of the Seismological Society of America*, 104(3):1122–1180.
- Flück, P., Hyndman, R. D., and Wang, K. (1997). 3-D dislocation model for great earthquakes of the Cascadia subduction zone. *Journal of Geophysical Research*, 102(B9):20539–20550.
- Fornberg, B. and Flyer, N. (2015). *A Primer on Radial Basis Functions with Applications to the Geosciences*. Society for Industrial and Applied Mathematics, Philadelphia.
- Frank, C. F. (1966). Deduction of earth strains from survey data. *Bulletin of the Seismological Society of America*, 56(1):35–42.
- Gladwin, M. T., Gwyther, R. L., Hart, R., Francis, M., and Johnston, M. J. S. (1987). Borehole tensor strain measurements in California. *Journal of Geophysical Research: Solid Earth*, 92(B8):7981–7988.
- Hines, T. T. and Hetland, E. A. (2016). Rapid and simultaneous estimation of fault slip and heterogeneous lithospheric viscosity from post-seismic deformation. *Geophysical Journal International*, 204(1):569–582.
- Holt, W. E. and Shcherbenko, G. (2013). Toward a Continuous Monitoring of the Horizontal Displacement Gradient Tensor Field in Southern California Using cGPS Observations from Plate Boundary Observatory (PBO). *Seismological Research Letters*, 84(3):455–467.
- Holtkamp, S. and Brudzinski, M. R. (2010). Determination of slow slip episodes and strain accumulation along the Cascadia margin. *Journal of Geophysical Research: Solid Earth*, 115(4):1–21.
- Kato, T., El-Fiky, G. S., Oware, E. N., and Miyazaki, S. (1998). Crustal strains in the Japanese islands as deduced from dense GPS array. *Geophysical Research Letters*, 25(18):3445–3448.
- Kohn, R. and Ansley, C. (1987). A new algorithm for spline smoothing based on smoothing a stochastic process. *SIAM journal on scientific and statistical computing*, 8(1):33–48.
- Langbein, J. (2004). Noise in two-color electronic distance meter measurements revisited. *Journal of Geophysical Research: Solid Earth*, 109(4):1–16.
- Langbein, J. (2008). Noise in GPS displacement measurements from Southern California and Southern Nevada. *Journal of Geophysical Research: Solid Earth*, 113(5):1–12.
- Langbein, J. and Johnson, H. (1997). Correlated errors in geodetic time series: Implications for time-dependent deformation. *Journal of Geophysical Research*, 102(B1):591–603.
- Mackay, D. J. C. (1998). Introduction to Gaussian processes. *Neural Networks and Machine Learning*, 168(1996):133–165.
- McCaffrey, R., King, R. W., Payne, S. J., and Lancaster, M. (2013). Active tectonics of northwestern U.S. inferred from GPS-derived surface velocities. *Journal of Geophysical Research: Solid Earth*, 118:709–723.
- McCaffrey, R., Qamar, A. I., King, R. W., Wells, R., Khazaradze, G., Williams, C. A., Stevens, C. W., Vollick, J. J., and Zwick, P. C. (2007). Fault locking, block rotation and crustal deformation in the Pacific Northwest. *Geophysical Journal International*, 169(3):1315–1340.
- McGuire, J. J. and Segall, P. (2003). Imaging of aseismic fault slip transients recorded by dense geodetic networks. *Geophysical Journal International*, 155:778–788.

- Murray, M. H. and Lisowski, M. (2000). Strain accumulation along the Cascadia subduction zone in western Washington. *Geophysical Research Letters*, 27(22):3631–3634.
- Ohtani, R., McGuire, J. J., and Segall, P. (2010). Network strain filter: A new tool for monitoring and detecting transient deformation signals in GPS arrays. *Journal of Geophysical Research: Solid Earth*, 115(12):1–17.
- Prescott, W. H. (1976). An extension of Frank’s method for obtaining crustal shear strains from survey data. *Bulletin of the Seismological Society of America*, 66(6):1847–1853.
- Press, W. H., Flannery, B. P., Teukolsky, S. A., and Vetterling, W. T. (2007). *Numerical Recipes: The Art of Scientific Computing*. Cambridge University Press, Cambridge, 3 edition.
- Rasmussen, C. E. and Williams, C. K. I. (2006). *Gaussian processes for machine learning*. The MIT Press.
- Sandwell, D. T. and Wessel, P. (2016). Interpolation of 2-D vector data using constraints from elasticity. *Geophysical Research Letters*, pages 1–7.
- Savage, J. C., Prescott, W. H., and Gu, G. (1986). Strain accumulation in southern California, 1973–1984. *Journal of Geophysical Research*, 91(B7):7455–7473.
- Schmalzle, G. M., McCaffrey, R., and Creager, K. C. (2014). Central Cascadia subduction zone creep. *Geochemistry, Geophysics, Geosystems*, pages 1515–1532.
- Schmidt, D. A. and Gao, H. (2010). Source parameters and time-dependent slip distributions of slow slip events on the Cascadia subduction zone from 1998 to 2008. *Journal of Geophysical Research: Solid Earth*, 115(4):1–13.
- Segall, P. and Mathews, M. (1997). Time dependent inversion of geodetic data. *Journal of Geophysical Research*, 102(B10):22391–22409.
- Shen, Z., Wang, M., Zeng, Y., and Wang, F. (2015). Optimal Interpolation of Spatially Discretized Geodetic Data. *Bulletin of the Seismological Society of America*, 105(4):2117–2127.
- Shen, Z. K., Jackson, D. D., Ge, B. X., and Bob, X. G. (1996). Crustal deformation across and beyond the Los Angeles basin from geodetic measurements. *Journal of Geophysical Research*, 101(B12):27927–27957.
- Shen, Z. K., King, R. W., Agnew, D. C., Wang, M., Herring, T. A., Dong, D., and Fang, P. (2011). A unified analysis of crustal motion in Southern California, 1970–2004: The SCEC crustal motion map. *Journal of Geophysical Research: Solid Earth*, 116(11):1–19.
- Shu, C., Ding, H., and Yeo, K. (2003). Local radial basis function-based differential quadrature method and its application to solve two-dimensional incompressible NavierStokes equations. *Computer Methods in Applied Mechanics and Engineering*, 192(7-8):941–954.
- Tape, C., Musé, P., Simons, M., Dong, D., and Webb, F. (2009). Multiscale estimation of GPS velocity fields. *Geophysical Journal International*, 179(2):945–971.
- Tolstykh, A. I. and Shirobokov, D. A. (2003). On using radial basis functions in a ”finite difference mode” with applications to elasticity problems. *Computational Mechanics*, 33(1):68–79.
- Wdowinski, S., Zhang, J., Fang, P., and Genrich, J. (1997). Southern California Permanent GPS Geodetic Array: Spatial filtering of daily positions for estimating coseismic and postseismic displacements induced by the 1992 Landers earthquake. 102(97):57–70.
- Wech, A. G., Creager, K. C., and Melbourne, T. I. (2009). Seismic and geodetic constraints on Cascadia slow slip. *Journal of Geophysical Research: Solid Earth*, 114(10):1–9.
- Wendland, H. (2005). *Scattered data approximation*.
- Wright, G. B. and Fornberg, B. (2006). Scattered node compact finite difference-type formulas generated from radial basis functions. *Journal of Computational Physics*, 212(1):99–123.
- Wyatt, F. (1982). Displacement of Surface Monuments: Horizontal Motion. *Journal of Geophysical Research*, 87(B2):979–989.
- Wyatt, F. K. (1989). Displacement of surface monuments: Vertical motion. *Journal of Geophysical Research*, 94(B2):1655–1664.