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Network Based Estimates of Strain-rate and Uncertainty in the Central U.S.

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Abstract

Paleoseismic observations in the New Madrid Seismic Zone (NMSZ) show sequences of large earthquakes with mean interevent times of ~ 500 years. Yet, current geodetic strain-rates are very low. Some studies have shown that average regional strain-rates are insignificantly different from zero. Others have found that differential velocities between selected sites are statistically significant. Clearly, a thorough understanding of errors in the GPS data is crucial in assessing the significance of any putative strain signal.

Some estimates of GPS velocity uncertainties are very low, less than 0.1 mm/yr with 10 years of data. Yet, residual velocities relative to rigid plate models in nominally stable plate interiors can be an order of magnitude larger. This discrepancy could be caused by underestimating low frequency time-dependent noise in position time series, such as random walk. We show that traditional estimators, based on individual time series, are insensitive to low-amplitude random walk, yet such noise significantly increases GPS velocity uncertainties. We developed a method for determining representative noise parameters in GPS position time series, by analyzing an entire network simultaneously, that we refer to as the Network Noise Estimator (NNE). We analyze data from the aseismic central-eastern US, assuming that residual motions relative to North-America, corrected for glacial isostatic adjustment (GIA), represent noise. The position time series are decomposed into signal (plate rotation and GIA), and noise components. NNE simultaneously processes multiple stations with a Kalman filter, and solves for average noise components for the network by maximum likelihood estimation. Synthetic tests show that NNE correctly estimates even low level random walk, thus providing better estimates of velocity uncertainties than conventional, single station methods. To test NNE on actual data, we analyzed a heterogeneous 15 station GPS network from the central-eastern US, assuming the noise is a sum of random walk, flicker and white noise. For the horizontal time series NNE

finds higher average random walk than the standard individual station based method, leading to velocity uncertainties a factor of 2 higher than traditional methods.

1 Report

Dmitrieva et al. [2015] developed a Network Noise Estimator (NNE) for estimating average noise parameters in GPS time series. We tested the performance of NNE relative to standard maximum likelihood (sMLE) methods, which operate on individual time series [e.g., Langbein, 2004], in estimating noise variances on synthetic data. We generated seven synthetic networks with 10 years of data at 10 stations (20 horizontal time series). Each time series is a sum of random walk, flicker noise and white noise. To test the method's performance at different ratios of random walk to flicker noise variance we keep white and flicker noise the same for all seven networks ($\sigma = 1$ mm, $\rho = 4$ mm/yr$^{0.25}$), but vary random walk from 0.1 to 1.5 mm/yr$^{0.5}$ for each test. Synthetic flicker noise is generated using the power-law covariance matrix.

The results of NNE and sMLE estimates are shown in Figure 1. Since sMLE estimates random walk, flicker and white noise for every time series, while NNE provides a single set of average parameters for the whole network we compare network estimates with median and quartile sMLE estimates. Both methods estimate white noise and flicker noise well for all values of random walk variance. However, NNE outperforms sMLE in estimating the random walk variance. The lower the random walk, the more sMLE underestimates its value. For example, for a random walk variance of $\tau = 0.5$ mm/yr$^{0.5}$, sMLE estimates zero random walk variance in 75% of the cases, whereas the NNE estimate is remarkably similar to the true value. Even for larger values of random walk, sMLE underestimates random walk, while NNE estimates more accurate values of τ. sMLE estimates become more accurate when random walk increases in amplitude. We conclude that sMLE may not detect low level random walk even when it is present in the data.

We calculate velocity uncertainty from the noise estimates. Not surprisingly, for all the cases when sMLE underestimated random walk, the estimated velocity uncertainty is also underestimated (Figure 1). For example, for random walk $\tau = 0.5$ mm/yr$^{0.5}$, the median sMLE velocity uncertainty is 0.13 mm/yr, while the true value is 0.21 mm/yr, which is 1.8 times higher. For $\tau = 1$ mm/yr$^{0.5}$ the median sMLE velocity uncertainty is 0.19 mm/yr, while the true value is 0.35 mm/yr. Once random walk is large, 1.5 mm/yr$^{0.5}$, the discrepancy between sMLE estimated velocity uncertainty and the true value is smaller (0.41 vs 0.5 mm/yr, only 1.2 times higher). The NNE estimates are much closer to the true value for all values of τ.

We applied the NNE to GPS time series from the central and eastern U.S. The network is small (15 stations) and heterogeneous in terms of station quality. Thus, the derived network noise estimates are *not* representative of high quality geodetic stations. Future work will incorporate more stations and subdivide them in terms of monument and other characteristics. However, application of the NNE to actual data, and in particular, comparison with standard MLE approaches is informative.

All the GPS data used in the preliminary study were processed with release 6.1 of the GIPSY software from the Jet Propulsion Laboratory. Non-fiducial daily GPS station coordinates were estimated using a precise point-positioning strategy [Zumberge et al., 1997]. The day-to-day scatter of the 3-D continuous site locations with respect to station locations averaged over 30-day-long windows for each site averaged 2 mm (1σ) in the horizontal components and 4-6 mm in the vertical components prior to any correction for common mode errors. The day-to-day scatter was reduced to 1 mm and 3 mm in the horizontal and vertical components,

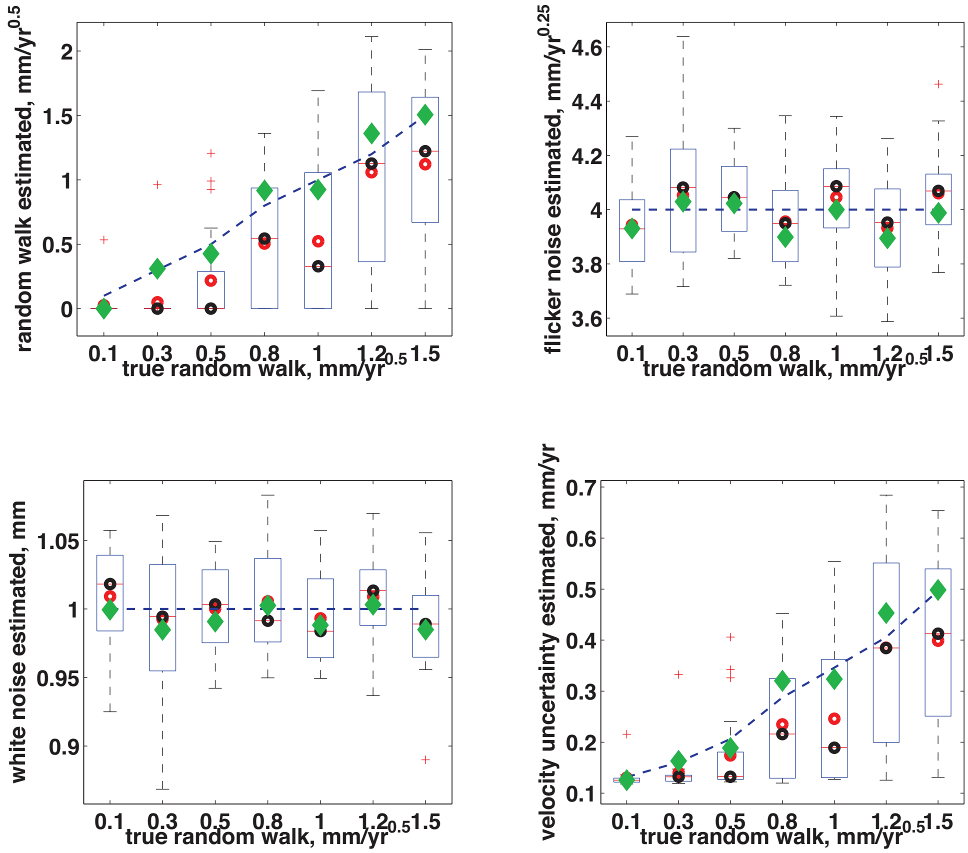

Figure 1: Estimates of noise components from NNE and sMLE compared to true values (synthetic data). Box plots show the distribution of sMLE noise estimates for 20 time series. Red central mark with a black circle indicates the median, box edges mark the 25th and 75th percentiles, whiskers include the most extreme data, but exclude outliers shown by red stars. The average sMLE estimate is shown with a red circle. Green diamonds show NNE estimates of the parameters. Blue dashed lines indicate true values.

respectively, after correcting station coordinates for spatially coherent, common-mode noise following Márquez-Azúa and DeMets [2003].

The positions are rotated into the North American reference frame from ITRF2008. We chose 15 stations with the longest time series (spanning between 10 and 20 years; the average length is 14 years) and few data gaps. Outliers greater than 6 mm were removed using a median filter with a window of 20 days. Seasonal signals were removed with a notch filter with central period/bandwidth of 1/0.25 years, which removes the annual as well as the draconic period.

We interpolated the predicted displacement due to GIA from the SNARF (Stable North American Reference Frame) model [Blewitt and et al, 2005, Hill et al., 2010] onto the station locations using 2D cubic spline interpolation (Figure 3), and then subtract it from the time series. The time series after the corrections described above are plotted on Figure 2. We first analyze the cleaned time series as described above, and next analyze the those with common-mode errors removed following the approach of Márquez-Azúa and DeMets [2003].

The stations have various monument types, purposes, and quality. Six of the sites are maintained by state transportation departments (VCAP, WIL1, PSU1, DNRC, HIPT and STKR), six are maintained by NOAA/ESRL (WLCI, BLKV, WDLM, DQUA, BARN and PATT), two

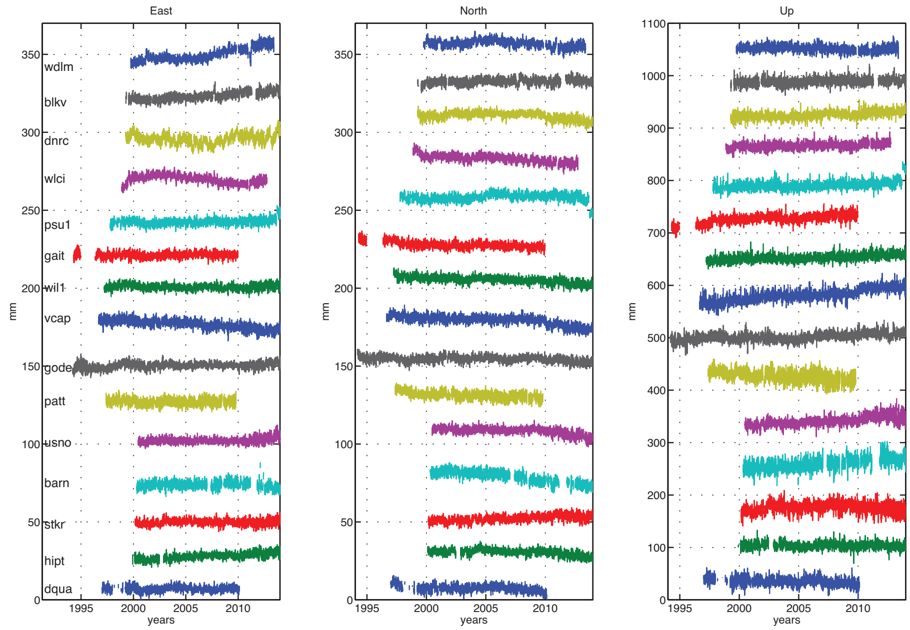

Figure 2: East, North and Up components of daily GPS position time series used in this paper. Station names are on the left. Arbitrary offsets for clarity. Note that the y-axis scale is different for horizontal and vertical components.

by NGS (GAIT and USNO) and one by NASA (GODE). The most common type of the monumentation is a steel mast on the top of a building (VCAP, WIL1, GAIT, PSU1, DNRC, HIPT and STKR), four stations are located on an antenna on the corner of a chain link fence (WLCI, WDLM, DQUA and PATT), two stations are monumented on concrete pillars with concrete bases (GODE and BLKV), one station is installed on a steel mast in concrete base (BARN) and one antenna is installed on a rod in a mortar rooftop parapet (USNO).

First, we analyzed the horizontal time series. We ran NNE on north and east components simultaneously. With NNE we found random walk τ=0.82 mm/yr$^{0.5}$, flicker noise ρ = 3.96 mm/yr$^{0.25}$, and white noise σ = 1.05 mm. NNE and sMLE results are compared in Figure 4. The NNE results for white and flicker noise are generally in agreement with the median of the sMLE results, however our estimate for random walk is substantially higher. The median of the sMLE random walk estimates is zero, while the mean is 0.29 mm/yr$^{0.5}$. Using the NNE estimates, the predicted velocity uncertainty is 0.29 mm/yr with 10 years of data and 0.23 mm/yr for 15 years of data. For the median sMLE estimates the predicted velocity uncertainties are 2 to 3 times lower: 0.12 mm/yr for 10 years of data and 0.08 mm/yr for 15 years.

We also analyzed the vertical time series. NNE finds no random walk, flicker noise ρ = 7.92 mm/yr$^{0.25}$, and white noise σ = 2.34 mm. These estimates lead to predicted velocity uncertainties of 0.45 mm/yr with 10 years of data. sMLE estimates are in good agreement with NNE for the vertical data.

There is considerable evidence that flicker and white noise are spatially correlated [Amiri-Simkooei, 2009]. Removing common-mode error decreases flicker noise in time series [Williams et al., 2004, Langbein, 2012]. We run NNE on the data but with common-mode removed based on the approach of Márquez-Azúa and DeMets [2003]. The most significant change in the estimated parameters is in the flicker noise. For the horizontal time series the flicker noise

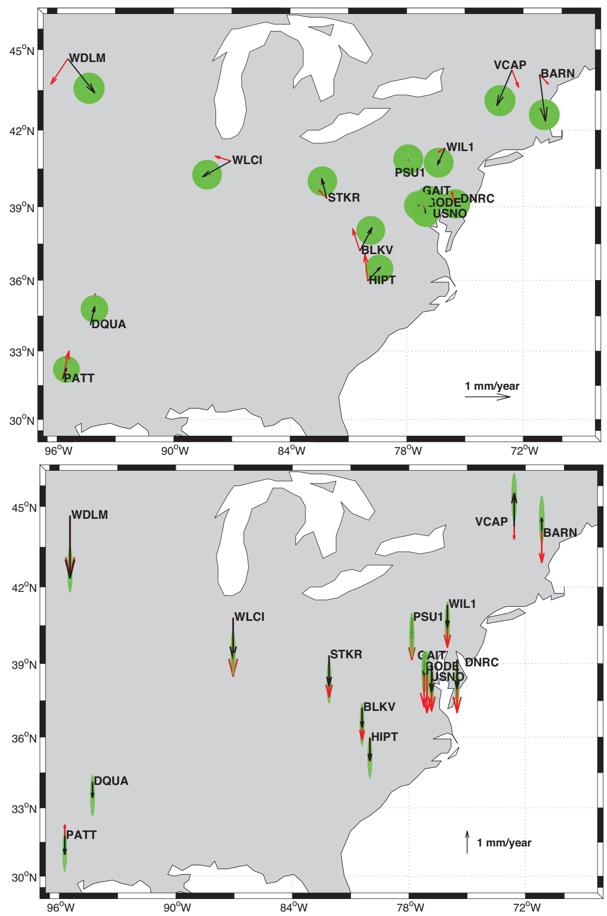

Figure 3: GPS stations used in the preliminary estimation with velocities (prior to removal of common mode errors) in fixed North American reference frame (black vectors). The top panel shows horizontal velocities, the bottom panel shows vertical. The interpolated GIA velocities (from SNARF model) are in red, the error ellipses (95% confidence) for velocities calculated from the estimated noise parameters (for 15 years of data) are shown in green.

decreased from 3.96 mm/yr$^{0.25}$ to 2.55 mm/yr$^{0.25}$ after the removal of common mode errors. For the vertical flicker noise decreased from 14.15 mm/yr$^{0.25}$ to 7.91 mm/yr$^{0.25}$ after common-mode error removal. The white noise did not change significantly and the random walk estimate was slightly higher for the common mode corrected data in the horizontal (0.95 mm/yr$^{0.5}$ vs 0.82 mm/yr$^{0.5}$ originally) and significantly higher for the common mode corrected vertical (2.21 mm/yr$^{0.5}$ vs 0 mm/yr$^{0.5}$).

The main advantage of the NNE comes from maximizing the likelihood of the fit to the full network. As we have seen from the simulations, the mean of the individual time series maximum likelihood estimates is not equivalent to the network maximum likelihood estimate. While it is possible to compute the likelihood for a network without the Kalman filter, the Kalman filter based network approach offers other advantages in that inclusion of spatial correlation should be straightforward, and more general seasonal models can be implemented [Murray and Segall, 2005].

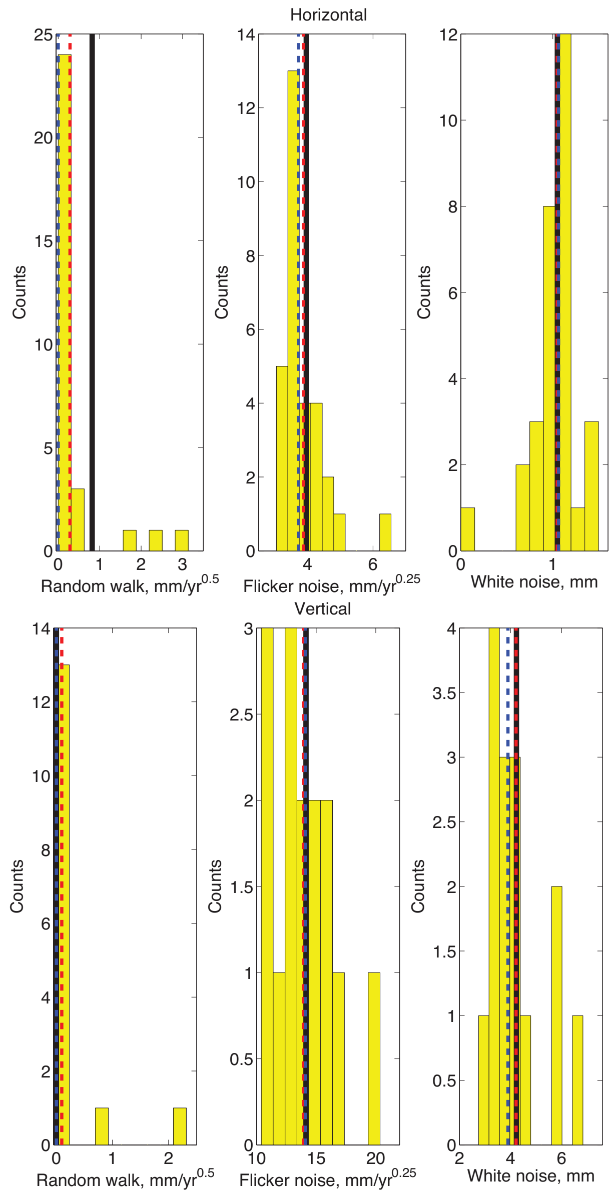

Figure 4: NNE and sMLE noise estimates of horizontal (top) and vertical (bottom) time-series. Yellow histograms show the distribution of noise parameters as estimated by sMLE. The mean sMLE noise parameter estimate is shown with a red dashed line, median is shown with a blue dashed line. NNE estimates are shown with black solid lines.

1.1 Conclusion

Based on synthetic tests, NNE provides accurate estimates of random walk variance, even with weak random walk. We therefore view NNE as a significant improvement over standard MLE approaches, in determining *representative* values of noise parameters. While network estimates are intrinsically averages, we suggest that NNE is beneficial in accurately estimating random walk for groups of stations with with similar monument quality and soil type.

Preliminary NNE results with a small, very heterogeneous network of horizontal GPS time series from the central and eastern US show larger random walk than estimated by standard

MLE. Since even low values of random walk can greatly affect velocity uncertainty, previous estimates of velocity uncertainty may be optimistic. For example with 10 years of data, standard estimates yield 1σ uncertainties of 0.12 mm/yr, whereas the network estimates are 0.29 mm/yr, 2.4 times higher than traditional estimates.

We suggest that NNE can be used to develop representative error models for continuous GPS sites. This will lead to improved uncertainties in derived station velocities.

2 Bibliography (exclusive of abstracts) supported by this award

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