Review Details: Cascadia Daily GNSS Time Series Denoising: Graph Neural Network and Stack Filtering

Walter Szeliga

Completed: 2025-01-08 12:15 PM
Recommendation: Revisions Required

Reviewer Comments

For author and editor

In “Cascadia Daily GNSS Time Series Denoising: Graph Neural Network and Stack Filtering”, the authors propose a novel approach to GNSS network time series denoising using a graph neural network. The problem of common mode noise in GNSS time series has been recognized for more than two decades. The authors consider a new approach to identifying network-wide common mode noise in collections of GNSS time series and compare this new approach to a few existing approaches. The identification and removal of common mode noise in GNSS time series is complicated by the fact that signals of interest, with actual geophysical sources, tend to have regionally similar waveforms. GNSS noise also has some of these qualities, in part due to errors in clock and orbit predictions for satellites in the common view of those stations. Thus, common mode noise detection algorithms have a potential to remove signals of interest while also removing actual noise. The authors explore an approach using a graph neural network where the graph consists of 8 nodes per station connecting stations with distances greater than 400 km from each other. These nodes are then trained on the time series and predictions of the expected regional time series (the noise in this case) are produced. Ten realizations of regional (noise) time series are then created from the trained graph neural network and subtracted from the actual time series, producing ten de-noised time series. These time series are then averaged to produce a single denoised time series for each station. For the Cascadia region, where one major signal of interest is slow slip, the authors compare their graph neural network approach with a classic Wdowinski time series stacking, a stacking based on proximity to tremor (a proxy for the location of slow slip), and stacking based on inter-station distance. Their results suggest that a graph neural network approach provides a viable alternative to commonly used stack-based denoising, albeit at a slightly greater computational expense.

This exploration of machine learning denoising for GNSS time series is an important contribution and would provide future investigators with an additional tool for investigating small amplitude geophysical signals in GNSS time series. To me, the most important contribution is the confirmation that existing stacking-based denoising techniques also provide reasonable results. As mentioned by the authors, one difficulty in assessing denoising algorithms is defining and identifying what is actually noise in GNSS time series. This difficulty is highlighted in Figures 5, S1, S2, where the average denoised time series using the classic Wdowinski approach is identically zero, by definition. This difficultly makes definitive quantitative assessment of the denoising approaches difficult. However, the authors do provide a nice assessment of the effect of each denoising technique on slow slip signals. Overall, I feel that this manuscript should be published with minor revisions to fix typographical errors.

Below are some specific comments:

Line 44: While the 70% and 30% numbers (also mentioned on line 568) are hinted at in section 3.1, the reader has to try to cobble together values across paragraphs to see where these values come from. In fact, I can only do this for UNR where I get (4.85-1.45)/4.85 = 70% (line 421). A more explicit statement of how the 70% and 30% improvement is calculated in this section would help the reader.

Line 65: "…in the Central Washington dataset, allow to more accurately…" reads awkwardly. Also, more of a question for the editor, but does one have to redefine acronyms like GNN again in the non-technical abstract?

Line 78: missing the word “have”, in “…episodes of slip on a fault that [have] much slower rupture and slip…”

Line 93: The citation is listed as Melgar et al., 2019, is this supposed to read Melgar et al., 2020?

Line 120: This sentence mentions static and clock delays. Perhaps it’s just quibbling over specific words, but I’m not sure what is meant by static delays and I assume clock delay really means receiver clock offset? The use of the word delay here seems different from the typical convention. I typically think of clocks as being offset but the troposphere as delaying.

Line 128: The word “of” is missing in “…challenging to effectively utilize estimates [of] ionospheric activity…”

Line 139: There is an unnecessary comma after “natural signals”

Line 313: There is a mention of an SSE offset metric, but what metric is that? Is this referring to Figure 8?

Line 319: Since “significant” has a more precise meaning in statistics, I assume what is intended here is “obvious” rather than “significant”?

Line 321–322: It’s not really relevant here to state what software package variable type is used for storage. I don’t think it would affect the outcome of the calculation if xarray datasets were used rather than pandas dataframes or just plain-old python lists.

Line 344: Are the patches spatial patches? Do you mean spatially proximal stations that have noise characteristics that cancel each other out?

Line 402–403; This sentence mentions the peak amplitudes of the raw data. That word choice suggests that a spectrum is involved somehow, or that there are obvious sinusoidal waves in the time series. Perhaps referring to the variance of the detrended time series would be better. Also, in many places the term “raw data” is used when it seems as if this is detrended data. I can see that they are “raw” in the sense that they haven’t been denoised yet, but “raw” is often used to denote a time series that still has a velocity component in a coherent reference frame.

Figure 7: What does CME stand for?

Line 619: “couple” should be “could” in “These two steps [could]"

Review Details: Cascadia Daily GNSS Time Series Denoising: Graph Neural Network and Stack Filtering

Hongyu Sun

Completed: 2024-11-20 02:41 PM
Recommendation: Revisions Required

Reviewer Comments

For author and editor

The manuscript uses a Graph Neural Network (GNN) to denoise GNSS time series data and compares its performance to a traditional method, stack filtering. The topic is relevant and important. While the performance of the GNN may not be better than that of stack filtering methods in some cases, the numerical experiments and their findings are valuable and worth publication. Below, I provide several suggestions to improve the manuscript and raise some questions that may help clarify key points for readers.

1. How did you construct the desired output for training, the signal without noise? I could not find a clear description of this in the data section.

2. It is great that the manuscript presents denoised results in different ways, but including an example demonstrating how the denoised data

may help identify Slow Slip Events (SSE) would greatly strengthen the manuscript.

3. While the manuscript compares GNN with stack filtering (a non-machine learning method), it may be necessary to benchmark against prior deep learning approaches, such as those by Thomas et al. (2023) and Costantino et al. (2024). Specifically, a comparison with the single-station method in Thomas et al. (2023) could highlight the advantages of using GNN with multiple stations. In addition, Costantino et al. (2024) also employs GNN, which is closely related to this work.

Reference
Thomas, A., Melgar, D., Dybing, S. N., & Searcy, J. R. (2023). Deep learning for denoising 858 High-Rate Global Navigation Satellite System data. Seismica, 2(1).
Costantino, Giuseppe, et al. "Denoising of Geodetic Time Series Using Spatiotemporal Graph Neural Networks: Application to Slow Slip Event Extraction." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (2024).

4. The use of GNN for seismic and geodetic data has been explored before. I suggest including a brief review of representative applications to give readers a broader understanding of the field.

5. I also have some question regarding the correlation of SSE and Common Mode Noise (CME) across stations:
(1) Both SSE and CME may show correlations across stations. How does the GNN distinguish between these and ensure that stations at relatively larger distances are not falsely treated as recording the same SSE?
(2) You mentioned that a 400 km distance was determined empirically through edge testing. Could you elaborate on the empirical testing? Did you simulate SSEs to determine detectability at different distances?
(3) In Figure 7, where 400 km is used to construct the graph, all stations seem fall within this distance. If CME within this “small” area below 400 km has been removed, does this imply that SSEs within the same area might also be inadvertently removed?

6. After denoising with GNN, do you plan to use further processing steps to handle noise specific to individual stations in practical applications?

7. Including geographical locations of stations as node features might enhance performance, as suggested in van den Ende and Ampuero (2020, GRL).

Reference
van den Ende, Martijn PA, and J-P. Ampuero. "Automated seismic source characterization using deep graph neural networks." Geophysical Research Letters 47.17 (2020): e2020GL088690.

8. Including learning curves would provide a better understanding of the model’s training process and convergence behavior.

9. For the Schematic Plot in Figure 2, (1) The number of records in the panel c does not match the number of input stations on the map in panel a. Using a consistent station number would improve clarity. I also suggest using consistent geometry between the station locations on the map and the GNN nodes. (2) Why is the target station not included as one of the input stations?

10. Line 287: “During the training process, dynamic random masks are created for each batch, selecting 30% of all nodes (GNSS stations).”
Are the masked nodes the target stations shown in Figure 3?
You mentioned: “The absence of a self-loop prevents the direct use of the signal itself.” What is the drawback of directly using the signal from input stations?

11. Figure 5: The second-row denoising result is missing.

12. Figure 7: Why is the segment before 2015-12-26 not considered CME? It also shows a consistent feature among stations. How do you identify CME in the data?

13. Figure 9: The caption is incorrect. The order of GNN and baseline is inconsistent between the plots and the caption.

14. Line 619: “Couple” should be corrected to “could.”

15. "The average horizontal offset of the UNR and CWU networks is reduced by 70% and 30%, respectively, after denoising for the GNN, and more than 95% for the stack filtering method."
Why does GNN show different performance across the UNR and CWU datasets? Any insights?

I hope that these comments are helpful, and I look forward to seeing a revised version of the manuscript.

Sincerely,
Hongyu Sun