

Fusion of Multi-Track InSAR Observations for Structural Displacement Estimation

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Abstract. This paper introduces a novel framework for reconstructing the displacements of civil structures using multi-track InSAR data, built upon a recursive Kalman Filter (KF) approach. While InSAR has proven to be a powerful technique for detecting milli-metric ground and structural displacements, its use in Structural Health Monitoring (SHM) is often limited by the one-dimensional nature of Line-of-Sight (LOS) measurements and the fragmented availability of satellite acquisitions. These limitations are overcome in this work by fusing multiple LOS observations from different viewing geometries—specifically, ascending and descending tracks from the European Ground Motion Service (EGMS)—into a unified three-dimensional displacement estimate. The proposed methodology is applied to the Schottwien Viaduct in Austria, a major prestressed concrete bridge. Four independent EGMS datasets are used, and the KF is employed to integrate their information into three-directional displacement time series. The resulting reconstruction provides insights into the structural behaviour of the bridge, demonstrating the method’s effectiveness and its potential for SHM.

Keywords: InSAR, European Ground Motion Service, Sentinel-1, Displacement, Structural Health Monitoring, Multi-Orbit Fusion, Kalman Filter

1 Introduction

Interferometric Synthetic Aperture Radar (InSAR) has emerged as a powerful tool capable of detecting millimetric displacements over large areas, with no need for ground instrumentation [1, 2]. In particular, the European Ground Motion Service (EGMS), based on Sentinel-1 SAR data, provides public, harmonized displacement time series across Europe, offering an unprecedented opportunity for wide-scale infrastructure monitoring [3, 4]. However, InSAR measurements are inherently one-dimensional, capturing displacements only along the satellite’s Line of Sight (LOS) [5, 6]. As a result, retrieving full three-dimensional (3D) displacement vectors from InSAR requires the combination of observations from multiple viewing geometries—typically, one ascending and one descending track [7, 8]. Despite this, the fusion of such data is far from straightforward. A common simplification adopted in literature and practice is to assume that the displacement in the North-South direction (which is poorly observable

from Sentinel-1's near-polar orbit) is negligible or zero. This allows projection equations to be solved for the East-West and vertical components but may lead to misleading results when the neglected component is non-negligible. Similarly, in the case of linear infrastructures, such as bridges, the transversal displacement is often assumed to be null. In addition, ascending and descending data are acquired at different times, usually spaced by several days. To reconcile these observations, displacement values are often interpolated in time, thus introducing uncertainty.

This paper presents a novel approach to overcome these issues through the application of a Kalman Filter (KF) [9]. The proposed framework integrates InSAR observations from multiple tracks in a dynamic, recursive estimation scheme that reconstructs the 3D displacement history of monitored points without the need to assume zero displacement in any direction. Unlike traditional fusion techniques, this method naturally handles asynchronous observations and is robust to missing data, while also incorporating the directionality and uncertainty of each LOS measurement through a time-varying observation model. The framework is applied to the Schottwien Viaduct, a prestressed concrete bridge in Austria, using four independent EGMS time series.

This paper is organized as follows. Section 2 presents the theoretical framework of the KF, detailing its formulation, the construction of the observation model, and the recursive estimation procedure for multi-geometry data fusion. Section 3 describes the case study of the Schottwien Viaduct, including the available EGMS datasets and their spatial and temporal characteristics. Section 4 reports the results of the KF application, comparing the performance with the conventional approach. Finally, Section 5 concludes the paper and outlines directions for future research.

2 Theoretical Framework and Application of the Kalman Filter for Multi-Track InSAR Monitoring

2.1 Kalman Filter Formulation

The KF is a linear recursive estimator designed to compute the best estimate of an evolving state vector based on a system model and a sequence of noisy observations. It operates in two stages: a prediction step, which advances the state estimate using the system model, and an update step, which corrects this estimate using new measurements. In this application, the state vector at time step k is defined as $\mathbf{x}_k = [d_L, d_T, d_V]^T$, where d_L , d_T , and d_V represent the longitudinal, transverse, and vertical displacements of the monitored structure, respectively. The state evolves according to the following discrete-time linear system: $\mathbf{x}_k = \mathbf{F}\mathbf{x}_{k-1} + \mathbf{w}_k$ and $\mathbf{z}_k = \mathbf{H}_k\mathbf{x}_k + \mathbf{v}_k$. Here, $\mathbf{F} \in \mathbb{R}^{3 \times 3}$ is the state transition matrix, assumed to be the identity matrix $\mathbf{F} = \mathbf{I}_3$ to reflect a quasi-static or slowly evolving displacement process. The vector $\mathbf{w}_k \sim N(0, \mathbf{Q})$ is the process noise, representing random variations in the state due to unmodeled influences or small environmental changes. The matrix $\mathbf{Q} \in \mathbb{R}^{3 \times 3}$ is the process noise covariance and is typically diagonal, with entries reflecting the expected variability of each displacement component. The vector $\mathbf{z}_k \in \mathbb{R}^{n_k}$ contains the LOS displacement available at time step k , and $\mathbf{v}_k \sim N(0, \mathbf{R}_k)$ is the corresponding

measurement noise, with $\mathbf{R}_k \in \mathbb{R}^{n_k \times n_k}$ the measurement noise covariance matrix. At each time step, the KF assimilates a set of LOS displacement observations derived from ascending and descending tracks of Sentinel-1. The number of available measurements at time step k , n_k , can vary with time due to data gaps or acquisition frequency. The generic observation vector is expressed as $\mathbf{z}_k = [z_k^{(1)}, z_k^{(2)}, \dots, z_k^{(n)}]^T \in \mathbb{R}^n$. Each scalar observation $z_k^{(i)}$ represents a one-dimensional projection of the 3D displacement vector $\mathbf{x}_k$, modulated by the InSAR acquisition geometry. Given an incidence angle $\theta^{(i)}$, azimuth angle $\alpha^{(i)}$, and structural orientation ϕ , defined in Fig. 1, the LOS projection reads:

$$z_k^{(i)} = \sin \theta^{(i)} \cos(\alpha^{(i)} - \phi) d_L - \sin \theta^{(i)} \sin(\alpha^{(i)} - \phi) d_T + \cos \theta^{(i)} d_V + v_k^{(i)} \quad (1)$$

This expression defines the i -th row of the observation matrix $\mathbf{H}_k \in \mathbb{R}^{n_k \times 3}$, as follows:

$$\mathbf{H}_k = \begin{bmatrix} \sin \theta^{(1)} \cos(\alpha^{(1)} - \phi) & -\sin \theta^{(1)} \sin(\alpha^{(1)} - \phi) & \cos \theta^{(1)} \\ \sin \theta^{(2)} \cos(\alpha^{(2)} - \phi) & -\sin \theta^{(2)} \sin(\alpha^{(2)} - \phi) & \cos \theta^{(2)} \\ \vdots & \vdots & \vdots \\ \sin \theta^{(n)} \cos(\alpha^{(n)} - \phi) & -\sin \theta^{(n)} \sin(\alpha^{(n)} - \phi) & \cos \theta^{(n)} \end{bmatrix} \quad (2)$$

The KF is initialized with an initial state estimate and covariance matrix. At each time step, it first predicts the structural displacement state using a quasi-static model, where the state transition matrix is assumed to be the identity matrix and the uncertainty is propagated through the process noise covariance. When InSAR LOS observations are available, the filter updates the predicted state by computing the Kalman gain, which weights the relative confidence in the model and measurements. The state estimate and its covariance are then corrected using the measurement residual. If no valid observations are available, only the prediction step is retained, allowing the filter to handle irregular or incomplete InSAR time series.

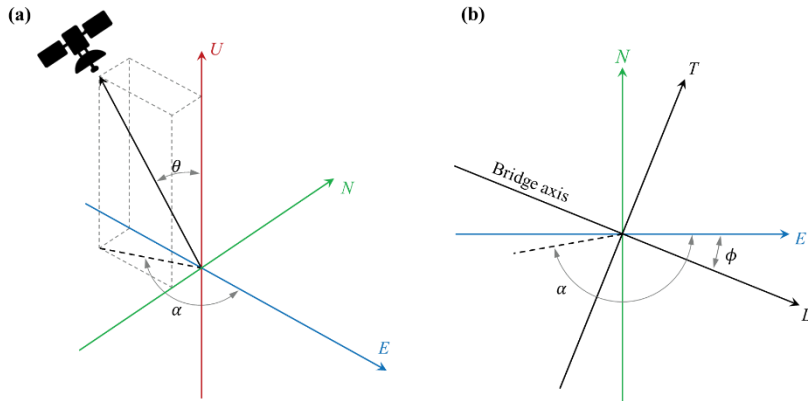


Fig. 1 Representation of (a) the global reference system and (b) its projection within the bridge local reference system (L,T,V) defined by the angle ϕ .

3 Case Study and InSAR Datasets

The Schottwien Viaduct, located along the S6 Semmering Expressway in Austria, is an outstanding example of prestressed concrete bridge engineering, see Fig. 2. Constructed between 1986 and 1989, the viaduct spans 632.50 m in length and reaches a height of approximately 130 m. It comprises four spans, i.e., 142.25 m, 250 m, 162.50 m, and 77.75 m—and is supported by three tall piers. The deck is transversely post-tensioned, and the entire structure exhibits a predominantly East-West orientation, forming an angle of 8.25° counterclockwise from the East axis.



Fig. 2. The Schottwien Viaduct, Austria.

The displacement analysis for the Schottwien Viaduct is based on publicly available time series provided by the EGMS. Four Sentinel-1 datasets are available from multiple viewing geometries. Specifically, the ascending datasets ASC073 and ASC146, and the descending datasets DSC022 and DSC124, spanning the period from 2018 to 2022. Fig. 3 displays the spatial distribution of the MPs across the viaduct for each dataset.

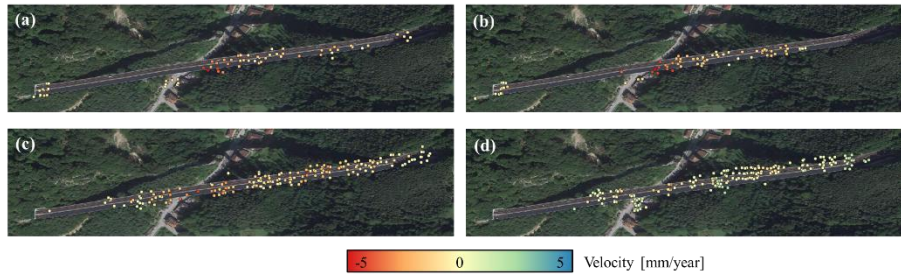


Fig. 3. InSAR data: Ascending datasets: (a) ASC073, (b) ASC146. Descending datasets: (c) DSC022, (d) DSC124.

While coverage is generally dense, the western portion of the bridge shows a scarcity of MPs in the ascending tracks. Nonetheless, the presence of MPs on the main spans and piers allows for integration of data across all four datasets. This study focuses on a single are of the bridge, as depicted in Fig. 4. The bridge is divided into a total of 16 areas. These same areas were considered in a previous study [10], the results of which are utilized here for comparative purposes and serve as a reference benchmark.

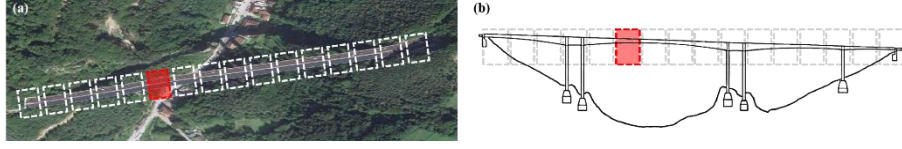


Fig. 4. Identification of the selected area from (a) top view and (b) longitudinal section.

This study focuses on two specific areas of the bridge, as depicted in Fig. 4. As detailed in [10], the central pier functions as a fixed constraint, dividing the bridge into two segments with different behaviour. During periods of elevated temperatures, thermal expansion causes the western segment of the deck to elongate westward, while the eastern segment extends eastward. The selected area, situated at a considerable distance from the fixed central pier, exhibits significant longitudinal displacements attributable to thermal expansion. The displacement time histories from each orbit of the MPs within each designated area are averaged to produce a representative time series for that area. This averaged time series serves as the input for the KF analysis.

4 Results

The KF was first applied using the EGMS LOS observations from the four available datasets (ASC073, ASC146, DSC022, DSC124). The state vector included the longitudinal, transverse, and vertical displacements, and the filter operated on an irregular temporal grid consistent with the acquisition dates of each track. A soft constraint was introduced in the form of a virtual measurement on the transverse displacement component [8], which is weakly constrained by the satellite LOS geometry. The virtual observation was implemented as a pseudo-measurement with a zero-mean value and large uncertainty, effectively expressing the assumption that transverse displacements are expected to be small but not strictly zero. The KF incorporated this constraint by extending the measurement model to include the virtual observation and by modifying the measurement noise covariance matrix accordingly. The filter was initialized as follows:

- Initial state estimate: $\mathbf{x}_0 = [0, 0, 0]^T$
- Process noise covariance: $\mathbf{Q} = \text{diag}(0.1, 0.1, 0.1)$
- Measurement noise covariance: $\mathbf{R} = \text{diag}(1, 1, 1, 1, 1000)$
- Initial estimation error covariance: $\mathbf{P}_0 = \mathbf{I}_3$

The measurement noise covariance matrix assigns high confidence (variance = 1) to the four actual EGMS LOS observations, and significantly lower confidence (variance = 100) to the virtual transverse measurement. This ensures that the constraint acts as a soft prior, influencing the filter only when no contradictory evidence exists in the real data. The reconstructed displacements for the studies area are shown in Fig. 5.

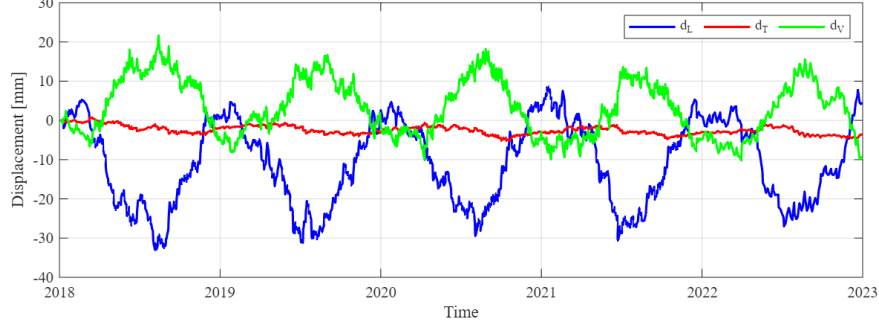


Fig. 5. Displacement time series obtained using the proposed KF approach.

The longitudinal displacements are predominant, with maximum elongation observed during summer months and minimum elongation in winter (in absolute terms). This behaviour is attributed to the relative position of the area concerning the fixed constraint. Conversely, vertical displacements exhibit maximum upward movement occurring in summer and downward movement in winter. The transversal displacement is relatively smaller and presents a weak seasonal trend as well.

To evaluate the consistency of the proposed method with conventional InSAR fusion techniques, the longitudinal and vertical displacements obtained through the KF were compared against results derived using the classical two-track decomposition presented in [10], see Fig. 6. In the traditional approach, data from one ascending (ASC146) and one descending (DSC022) dataset are combined under the assumption of null North–South displacement and using linear interpolation to align observations in time.

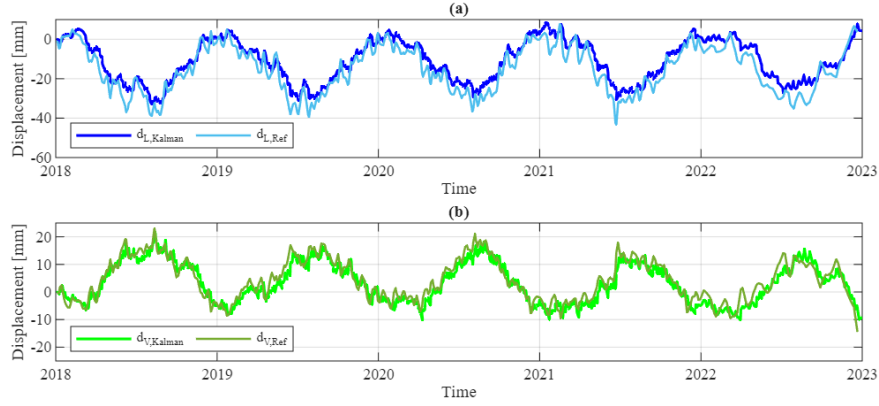


Fig. 6. Comparison of (a) Longitudinal and (b) Vertical displacements with reference values.

Given that the axis of the Schottwien Viaduct is nearly aligned with the East–West direction, the KF-estimated longitudinal displacement was compared with the East–West component derived from the classical method. The longitudinal displacement, aligned closely with the East–West axis due to the bridge's orientation, exhibits

remarkable agreement between the two methods, with discrepancies well within acceptable limits. Similarly, the vertical displacement estimates from both approaches display consistent trends and magnitudes, indicating that the incorporation of the soft constraint noticeably improves the estimation of these components.

While the current comparison demonstrates the efficacy of the soft-constrained KF in producing reliable displacement estimates, further validation using a local reference system or independent ground-based measurements would be beneficial to ascertain the performances of the method.

5 Conclusion

This study proposed a Kalman Filter (KF)-based framework for fusing multi-track EGMS InSAR time series to estimate three-dimensional structural displacements. The method addresses key limitations of conventional InSAR fusion, including the one-dimensional nature of LOS measurements, weak component observability, and temporal inconsistencies between different satellite orbits. The framework recursively integrates asynchronous LOS observations from multiple viewing geometries while accounting for missing data, measurement noise, and acquisition geometry. A key advantage of the proposed approach is that, through the introduction of a soft virtual-sensor constraint, it enables the estimation of the transverse displacement component, which is typically poorly observable or neglected in classical InSAR decomposition methods.

The approach was applied to the Schottwien Viaduct in Austria using four EGMS datasets. The results showed good agreement with a classical two-track decomposition method in the longitudinal and vertical directions, while additionally providing an estimate of the transverse component and demonstrating the benefits of the recursive formulation for multi-track and multi-temporal data fusion.

The study shows that the KF with soft constraints provides a robust and scalable tool for InSAR-based monitoring, allowing a more complete three-dimensional interpretation of bridge displacements. Future work will focus on validation with independent ground-based measurements, integration of external drivers such as temperature, and application to large-scale infrastructure networks.

Acknowledgments. This study was carried out as part of the program of activities outlined with the DPC-ReLUIIS 2024-2026 project – WP6 “Monitoring and satellite data”.

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