

Bayesian Data Fusion for Enhanced Monitoring of Bridge Displacements Using Satellite InSAR and Topographic Techniques

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Abstract. This paper introduces a Bayesian data fusion methodology for monitoring bridge displacements, using a synergistic combination of satellite Interferometric Synthetic Aperture Radar (InSAR) and topographic measurements. Focused on the Belprato 2 Viaduct affected by a slow-moving landslide, this research highlights the advantages of integrating multiple data sources to surpass the limitations of individual monitoring techniques. The results demonstrate substantial improvements in the accuracy and temporal resolution of displacement measurements, highlighting the utility of data fusion in structural health monitoring of aging infrastructures.

Keywords: Bayesian Data Fusion, Structural Health Monitoring, InSAR, Topographic Monitoring, Bridge Displacement Analysis, Landslide Impact Assessment, Infrastructure Safety, Remote Sensing

Introduction

Civil infrastructure health, particularly of bridges, is a critical component in maintaining economic stability and public safety across the globe. As these structures age and traffic volumes increase, the risks associated with potential structural failures escalate, necessitating robust and reliable monitoring techniques [1]. Traditionally, structural health monitoring (SHM) has relied heavily on periodic visual inspections and on-site measurement techniques. While these methods provide essential information, they are often labor-intensive, costly, and can subject to human error, limiting their effectiveness and scalability [2, 3].

The advent of Interferometric Synthetic Aperture Radar (InSAR) technology is pushing toward a transition in the SHM practice. InSAR offers a remote, non-invasive, costeffective means to detect and monitor displacements and deformations across extensive areas



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Media and Publishing Partner https://doi.org/10.58286/29688 with millimeter-level precision [4-6]. This technology has proven particularly valuable in inaccessible or hazardous locations, providing continuous monitoring without the need for physical presence of people or devices on the site [7].

However, despite its advantages, InSAR is not without limitations. Its effectiveness can be significantly diminished in complex terrain settings, such as mountainous regions, where satellite visibility and angle of incidence can restrict the accuracy and comprehensiveness of the data collected. Moreover, InSAR data is typically confined to the line-of-sight (LOS) measurements, which does not always provide a complete picture of three-dimensional structural movements. This limitation is particularly critical in areas like the Alps in Europe, where the topography can alter the satellite signal paths, leading to potential data inaccuracies [8].

To address these challenges, this paper introduces a novel methodology that integrates InSAR technology with traditional topographic monitoring techniques through a Bayesian data fusion approach. This integration leverages the extensive coverage of InSAR and the high accuracy of ground-based topographic measurements, creating a synergistic monitoring system that enhances the capabilities of each method. The Bayesian framework employed allows for the optimal fusion of these heterogeneous data sources, accounting for their respective uncertainties and sampling frequency, and providing a more robust and accurate assessment of structural health.

Our study is set against the backdrop of increasing environmental challenges and aging infrastructure, which collectively push the boundaries of traditional monitoring techniques. By adopting this innovative data fusion approach, we aim to demonstrate its effectiveness in providing detailed, accurate, and timely assessments of structural health, which are crucial for the proactive management and maintenance of critical infrastructure. The methodology is validated through the case study of the Belprato 2 Viaduct in Italy, a structure situated in a geologically sensitive area and affected by an extremely slow-moving landslide, making it an ideal candidate for demonstrating the benefits of our approach.

1. Methodology

This section outlines the methodology employed in integrating Interferometric Synthetic Aperture Radar (InSAR) data with traditional topographic measurements using a Bayesian data fusion approach. This method exploits the unique strengths of both monitoring technologies, enhancing the precision and reliability of structural displacement assessments.

The satellite data utilized in this study were acquired from the COSMO-SkyMed mission. These images are capable of capturing millimeter-level displacements across extensive areas, providing a comprehensive overview of structural changes over time. The InSAR data were processed using the Multi Temporal InSAR (MT-InSAR) method, which enabled us to identify and track Persistent Scatterers (PS) along the viaduct. These Persistent Scatterers provide measurement points that are highly and persistently visible by the SAR sensors carried by satellites. MT-InSAR calculates the displacements of PSs along the satellite's Line-of-Sight (LoS) from stacks of SAR images. Complementary to the InSAR data, high-resolution topographic measurements were obtained using a total station in a free configuration, which allows for a setup reusable for different bridges and precise measurement of three-dimensional displacement vectors. These measurements were conducted at specific points on the structure, equipped with optical prisms to facilitate accurate data collection. This method provides localized, high-accuracy displacement data, essential for detailed assessments of structural behavior.

To integrate the diverse datasets from InSAR and topographic monitoring, a Bayesian data fusion model was developed, incorporating the components described as follows. The

displacement model is linear with respect to its parameters (y_0, m, α) , where y_0 represents the model offset, *m* the displacement velocity, and α the apparent thermal coefficient. These parameters are treated as Gaussian-distributed random variables, allowing for the incorporation of data uncertainties and the application of the Bayesian updating process. The model reads as:

$$y = y_0 + m \cdot t + \alpha \cdot T \tag{1}$$

Prior distributions of parameters are based on previous studies and expert judgments regarding the expected behavior of the structure under observation and the geological context. These priors serve as the baseline for the Bayesian analysis, aiding in the interpretation and integration of the new data.

The likelihood function is designed to evaluate the compatibility of the observed data with the model predictions. Specifically, topographical measurements are represented in a Cartesian coordinate system (s, q, z), where s and z are the horizontal and vertical axis of the LoS vertical plane. Satellite InSAR measurements are unidirectional displacements along the LoS, l, which are included in the model through a decomposed into s and z components as per Equation 4, where θ is the incidence angle between the LoS and the vertical direction z of the investigated area.

$$l = -s \cdot \sin(\theta) + z \cdot \cos(\theta) \tag{4}$$

Figure 1 shows the topographic coordinate system (s, q, z) and the satellite coordinate system (v, q, l), which rotate the first into the second around the common axis q according to the angle θ .



Fig. 1. The rotation of the topographic coordinate system (s, q, z) into the satellite coordinate system (v, q, l) according to the rotation angle θ .

The likelihood function accommodates the different measurement uncertainties and sampling frequencies of these datasets. Given the linear-Gaussian nature of the model, the Bayesian updating process can be implemented through a closed-form solution, as detailed in Equations 2 and 3 [10]:

$$\boldsymbol{\Sigma}_{\boldsymbol{\phi}|\boldsymbol{y}} = \left[\boldsymbol{D}^{\mathrm{T}} \cdot \boldsymbol{\Sigma}_{\boldsymbol{y}|\boldsymbol{\phi}}^{-1} \cdot \boldsymbol{D} + \boldsymbol{\Sigma}_{\boldsymbol{\phi}}^{-1} \right]^{-1}$$
(2)

$$\boldsymbol{\mu}_{\boldsymbol{\phi}|\boldsymbol{y}} = \boldsymbol{\mu}_{\boldsymbol{\phi}} + \boldsymbol{\Sigma}_{\boldsymbol{\phi}|\boldsymbol{y}} \cdot \mathbf{D}^{\mathrm{T}} \cdot \boldsymbol{\Sigma}_{\boldsymbol{y}|\boldsymbol{\phi}}^{-1} \cdot (\boldsymbol{y}(\boldsymbol{\phi}) - \hat{\boldsymbol{y}}(\boldsymbol{\phi}))$$
(3)

Here, ϕ denotes the parameter vector, with μ_{ϕ} and Σ_{ϕ} being the prior mean vector and covariance matrix of parameters, respectively. $\mu_{\phi|y}$ and $\Sigma_{\phi|y}$ represent the posterior mean

vector and covariance matrix, respectively. **D** is the model's sensitivity matrix, and $\Sigma_{y|\phi}$ is the likelihood covariance matrix, reflecting the measurement uncertainties. **y** is the measurement vector, including all the acquired measurements from both topographic and satellite systems.

This approach utilizes the analytical expression derived from the Gaussian distribution properties, allowing for efficient and precise estimation of the posterior distributions of the model parameters. The analytical nature of our approach avoids the computational complexity and convergence issues often associated with iterative sampling methods like MCMC, making it highly efficient for real-time monitoring applications.

2. Case Study: Belprato 2 Viaduct

The Belprato 2 Viaduct, situated in the Isarco Valley along the A22 highway in Italy, serves as the focal point for validating the Bayesian data fusion methodology developed in this study. This viaduct is an exemplary candidate due to its exposure to an extremely slow-moving landslide, making it susceptible to gradual yet significant structural displacements.

The Belprato 2 Viaduct, situated in Italy's Isarco Valley and part of the A22 highway, is the case study for validating our proposed Bayesian data fusion method. This viaduct, affected by a slow-moving landslide, provides a complex yet ideal scenario for applying and testing our approach. It consists of one deck with two carriageways divided in nine spans on the northbound lane and twelve on the southbound, each with a length of about 35 meters, and constructed from prestressed reinforced concrete beams. Those spans are supported by full piers and half-piers, the latter directly contacting the moving slope, making it susceptible to displacement. Optical prisms installed on these piers have facilitated movement tracking through topographic monitoring, revealing different displacement rates among the piers, ranging from less than 1 mm/year to up to 11 mm/year.

A detailed geotechnical model of the landslide affecting the viaduct was developed by the University of Trento, incorporating surface, depth measurements, and on-site surveys. The landslide spans approximately 170,000 m², with a volume of about 5.5 million m³ and involves complex movement mechanisms that interact with the viaduct's foundation. Figure 1a shows the lateral view of the Berlprato 2 Viaduct and the extension of the landslide [9].



Fig. 2. (a) Belprato 2 Viaduct and landslide profile, (b) Pier 9 and optical prism.

The monitoring setup consists of a combination of topographic and InSAR monitoring. Optical prisms were installed on specific piers of the viaduct to facilitate precise topographic measurements. These prisms enabled the tracking of displacements through a total station, which was set up in a free configuration allowing for flexible and accurate data collection. Measurements were taken periodically, capturing the incremental movements of the viaduct's structure over time. As far as InSAR Monitoring is concerned, a series of 73 SAR images were acquired from January 2016 to December 2020 under the COSMO-SkyMed mission. These images, processed using the SarProZ software, helped identify PSs

along the structure, providing consistent and reliable data points for monitoring displacements. The images covered the area only from the descending orbit to avoid the foreshortening error, which is significant in this mountainous region.



Fig. 3. Map of the area of interest, with the number of piers, optical prisms and PSs highlighted.

Notably, InSAR monitoring cannot provide information on the orthogonal direction to the vertical plane of the LoS, in this case, the direction q. Therefore, our analysis omits this axis and focuses only on displacements along directions s and z. Topographical data solely provide displacement information in direction q; however, given the landslide movement's fortunate alignment with the LoS vertical plane in this particular case, displacements in s and z directions are enough for monitoring the landslide's effect on the bridge.

Measurement uncertainties are estimated at 5 mm for topographical and 10 mm for satellite measurements, realistic for such a study, with topographical data collected in a free station setup. Prior parameter distributions, independent of measurements and based on geological and geotechnical previous studies, incorporate considerations like landslide movement direction, slow landslide velocity (max 16 mm/year), average slope inclination (27°), and the absence of seasonal periodicity due to temperature and groundwater variations. Table 1 shows the model parameters' mean values and standard deviations a priori, assumed to be uncorrelated.

	S_0	Z_0	m_s	m_z	α_{s}	$lpha_{z}$
	[mm]	[mm]	[mm/year]	[mm/year]	[mm/°C]	[mm/°C]
μ	0.00	0.00	-7.60	-1.86	0.050	0.16
σ	100	100	3.80	0.93	0.025	0.032

Table 1. Mean values and standard deviations of parameters a priori.

3. Results and discussion

The integration of InSAR and topographic data using the Bayesian data fusion model yielded significant insights into the displacement experienced by the Belprato 2 Viaduct. This section presents the key findings from the fused data and highlight the differences when compared to the use of either dataset, satellite or topographic measurements alone.



Fig. 4. Displacements along the s and z directions obtained by applying the proposed method to the three different datasets of this case study: (a) and (b) datasets from satellite monitoring, (c) and (d) datasets from topographic monitoring, (f) and (g) data fusion between satellite and topographic monitoring datasets.

Figure 4 displays the prior and posterior results achieved by applying the method outlined in the preceding section to the three distinct datasets of this case study: Figures 4a and 4b show results using only the dataset of displacements obtained through satellite monitoring; Figures 4c and 4d show outcomes utilizing solely the dataset of displacements acquired via topographic monitoring; Figures 4e and 4f show results from the data fusion

method presented above, incorporating both satellite and topographic monitoring datasets. Figures in the first column illustrate displacements in the horizontal direction (*s*-axis), while those in the second column illustrate displacements in the vertical direction (*z*-axis).

One of the primary results from this study is the enhanced frequency and accuracy of displacement measurements obtained from combining the two datasets. The Bayesian data fusion model effectively combined the higher sampling frequency of InSAR data with the highly accurate local measurements from the topographic surveys. This integration allowed for a more detailed visualization of displacement along time and a higher accuracy in displacement trends, m_s and m_z , as highlighted by Table 2.

	<i>s</i> ₀ [mm]	z_0 [mm]	<i>m</i> s [mm/year]	m_z [mm/year]	α_s [mm/°C]	$lpha_z$ [mm/°C]				
Posterior with satellite measurements										
μ	0.93	-4.02	-8.24	-1.93	0.05	0.16				
σ	8.84	7.17	1.67	0.88	0.025	0.032				
Posterior with topographic measurements										
μ	-4.37	2.35	-9.64	-1.75	0.048	0.16				
σ	6.76	5.05	0.85	0.63	0.025	0.032				
Posterior with data-fusion method										
μ	-6.34	1.43	-9.29	-1.46	0.046	0.16				
σ	6.11	4.45	0.77	0.55	0.025	0.031				

Table 2. Mean values and standard deviations of parameters a posteriori

The quantitative analysis of displacements revealed several key trends. The fused data indicated that certain sections of the viaduct experienced displacements at a higher rate; this finding is crucial for understanding the impact of the landslide on the viaduct and prioritizing maintenance and intervention efforts. The consistency between InSAR and topographic measurements increased confidence in the reliability of the observed displacement patterns. Discrepancies that were initially observed in standalone datasets were resolved after applying the Bayesian fusion approach.

4. Conclusion

This study has demonstrated the significant advantages of employing Bayesian data fusion for the integration of InSAR and topographic monitoring data in assessing the structural health of civil infrastructures. The fusion of these distinct data types provided a more detailed and comprehensive analysis of the viaduct's displacements, overcoming the limitations inherent in each method when used independently.

The Bayesian data fusion approach effectively harnessed the strengths of both methods, yielding a richer, multidimensional understanding of structural displacements. This integrated approach enhanced the accuracy and temporal resolution of the displacement data and provided a continuous monitoring framework, which is crucial for the nature of structural health monitoring. This approach can significantly improve decision-making processes in infrastructure management, allowing for more informed and timely interventions. The benefit increase when including in the analysis archive SAR images, then sometimes go back in time since 2014, providing years of information of bridge displacements already measured.

The case study of the Belprato 2 Viaduct illustrates the practical benefits of data fusion approaches in real-world applications, particularly in complex structural systems like those affected by slow-moving landslides. Future studies will focus on extending this methodology to other infrastructures and exploring the integration of additional data types.

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