AutoSatBridge: Towards AI-Supported Bridge Monitoring Using Persistent Scatterer InSAR and High-Resolution TerraSAR-X Data

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Abstract:

Bridges are vital to national infrastructure, yet their inspection remains resource-intensive. The AutoSatBridge project addresses this challenge by integrating satellite-based Persistent Scatterer Interferometry (PSI), in-situ sensor data, and artificial intelligence (AI) into a unified monitoring framework. Using the A3 motorway bridge in Sinzing, Germany as a pilot site, the project combines high-resolution TerraSAR-X radar data with displacement and temperature measurements to detect structural deformations with high spatial and temporal resolution. A central focus lies in attributing PSI-derived signals to specific bridge components, enabling targeted analysis of structural changes like load responses or temperature influences. These results feed into a digital twin based on the Asset Administration Shell (AAS), facilitating real-time condition assessment and predictive maintenance. By combining Earth observation EO technologies with engineering expertise and AI, AutoSatBridge supports scalable, continuous structural health monitoring and contributes to the long-term resilience of transport infrastructure.

Keywords: Earth Observation (EO), Persistent Scatterer Interferometry (PSI), Digital Twin, Structural Health Monitoring, Artificial Intelligence (AI)

1 Introduction

Structural health monitoring (SHM) is essential for ensuring the safety, longevity, and resilience of civil infrastructure. Bridges, in particular, play a vital role in enabling economic activity and mobility, making their continuous monitoring a matter of national interest and international relevance. The importance of effective SHM is underscored by its contribution to sustainability objectives outlined in the UN Sustainable Development Goals (SDGs) [1], especially SDG 9 (“Build resilient infrastructure”) and SDG 11 (“Sustainable cities and communities”), as well as European Green Deal [2] targets for climate-resilient transport systems.

The ageing of road bridges in Germany is progressing steadily. The reasons for this are the increased volume of traffic as well as damage and the associated deterioration of the structure. To counteract this, structural inspections are carried out. They require close-range access and therefore are costly and time-consuming. In addition, areas of the road often have to be closed for the examination with the inspection vehicle. Damage is therefore only visible during the inspection 3-years intervals [3]. No surveillance takes place in between.

One solution for permanent information gathering is the use of monitoring. Targeted monitoring of existing damage is a widely used method for this. For predictive maintenance, however, changes to the structure must be detected before they cause major damage. Both classic monitoring systems with acceleration sensors or strain gauges and promising spaceborne monitoring methods such as Persistent Scatterer Interferometry (PSI) are being investigated for this purpose. As each system works on its own, research is being carried out into developing the standardization of data with the help of digital twins. The aim of the research project is to compare data from an in-situ measurement system and data collected from satellites and to determine whether this new approach can be used to monitor structures.

The Sinzing motorway bridge was selected as the test object. It crosses the river Danube between Regensburg and Nuremberg on the A3 motorway. The 930 m long structure consists of nine spans with a maximum span of 130 m and two independent steel deck girders, each 14.25 m wide [4]. The superstructures are supported on massive piers with a maximum height of 47 m. Due to the planned widening of the A3 to three lanes in each direction, the bridge will be replaced by a new structure in the medium term [4]. The bridge, which was completed and opened to the public in 1966, is showing signs of fatigue in various areas, in addition to regular bridge inspections, the motorway maintenance department carries out regular inspections [5]. Due to its size and the interest of the bridge operator, it is ideally suited for this research project.

Despite the advancement of satellite-based monitoring techniques such as Persistent Scatterer Interferometry (PSI), their application has mostly been retrospective [6], [7], [8] and was used to analyse structures after damage or collapse. This reactive paradigm limits the preventative potential of Earth observation (EO) technologies in infrastructure management. The AutoSatBridge project addresses this gap by developing a framework that combines high-resolution TerraSAR-X satellite data with domain knowledge from civil engineering and real-time in-situ sensor measurements. Using the A3 motorway bridge in Sinzing, Germany, as a demonstration site, the project aims to establish a proactive, component-level monitoring approach. By integrating EO data into digital twins and leveraging artificial intelligence (AI) for semantic analysis, AutoSatBridge paves the way toward scalable, continuous SHM solutions for critical infrastructure. Figure *1* depictes the schematics of integrating in-situ measurements with TerraSAR-X data into an Asset Administration Shell (AAS).

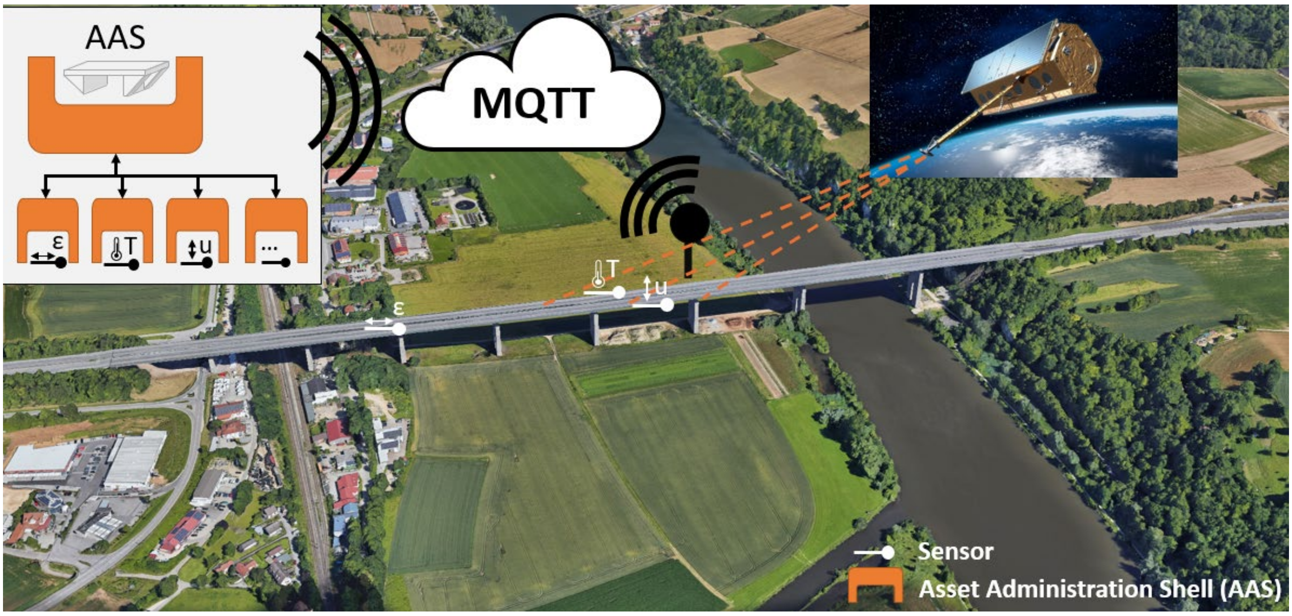

Figure 1: Data and in-situ sensor integration scheme for the A3 Sinzing motorway bridge into the Asset Administration Shell (AAS)

2 Remote Sensing Framework: PSI with TerraSAR-X

Spaceborne Synthetic Aperture Radar (SAR) systems enable consistent Earth surface observation regardless of lighting conditions or cloud cover, due to their use of microwave signals. These systems transmit radar pulses and receive backscattered complex valued signals from the surface. Man-made structures such as bridges, buildings or antenna towers with their multitude of rectangular features act as pronounced reflectors. Those elements appear as bright, point-like features due to their strong and stable backscatter. If those features exhibit a high phase stability across multiple SAR acquisitions they are referred to as Persistent Scatterers (PS) [9]. In case the phase of natural surfaces such as vegetation, bare soil, or non-urban areas, which show more homogeneous statistical backscatter behaviour pass statistical tests they are termed Distributed Scatterers (DS) [10].

SAR data consists of both amplitude and phase components of the returned radar signal. By co-registering two or more SAR images taken at different times from the same orbit, the phase differences between corresponding pixels can be computed. This phase difference, stored in an interferogram, contains information about surface topography, deformation, and atmospheric effects.

Persistent Scatterer Interferometry (PSI) exploits the temporal phase stability of PS points to estimate ground deformation and elevation with high precision [9]. DS are used to densify the resulting point cloud in the absence of PS. The interferometric phase of the i-th interferogram ϕ_{dint} is expressed as

$$\phi_{\mathrm{dint}} = \phi_{\mathrm{topo},x,i} + \phi_{\mathrm{defo},x,i} + \phi_{\mathrm{atmo},x,i} + \phi_{\mathrm{noise},x,i} \tag{1}$$

where the topographic phase term $\phi_{\mathrm{topo},x,i}$ accounts for the uncertainties of the digital elevation model (DEM). The phase term $\phi_{\mathrm{defo},x,i}$ reflects the phase contribution caused by deformation. Further phase components are attributed to the atmosphere $\phi_{\mathrm{atmo},x,i}$ and noise $\phi_{\mathrm{noise},x,i}$ of the i-th interferogram for scatterer x.

The topographic phase is given by

$$\phi_{topo,x,i} = \frac{4\pi}{\lambda R\, sin(\alpha)} B_n(x) \cdot H_{res} = K_h \cdot H_{res} \tag{2}$$

and can be interpreted as pure geometric depending only on the radar wavelength λ, the distance between the satellite and the detected object R, the incidence angle α as well as the baseline B_n of the interferogram and the residual height H_{res} with respect to the DEM. Furthermore, those constants are collected in K_h.

On the other hand, the phase attributed to deformation reflects the displacement between the two acquisitions forming the interferogram. Constants are collected in K_v.

$$\phi_{defo,x,i} = \frac{4\pi}{\lambda} v(x) \cdot t_i = K_v \cdot v(x) \cdot t_i \tag{3}$$

Combining Eq.(2) and Eq.(3) for all scatterers x in an interferogram i, the equations can be expressed as follows:

$$\Phi = K_h \cdot H_{\text{res}}^T + K_v \cdot T \cdot V^T + E \tag{4}$$

Collecting Eq.(4) for all interferograms leads to a system of linear equations

$$\begin{bmatrix} \phi_1 \\ \phi_2 \\ \vdots \\ \phi_n \end{bmatrix} = \begin{bmatrix} K_h \\ K_h \\ \vdots \\ K_h \end{bmatrix} \begin{bmatrix} K_v & T \\ K_v & T \\ \vdots & \vdots \\ K_v & T \end{bmatrix} \begin{bmatrix} H_{\text{res}} \\ V \end{bmatrix} \tag{5}$$

which can be solved for H_{res} and V. Where H_{res} is the correction for the DEM at location x and V is the displacement velocity.

In this framework, a stack of SAR scenes is co-registered by projecting the individual acquisitions onto a common geometry using a 5-meter resolution Digital Terrain Model (DTM), ensuring geometric alignment across all scenes. Subsequently, potential PS candidates are identified by calculating the amplitude dispersion index and coherence, which are statistical measures that reflect the temporal stability of a scatterer's amplitude and phase signal[11]. Interferograms are then generated relative to a designated reference scene.

In this study, high-resolution SAR data from Germany's TerraSAR-X [12] and TanDEM-X missions are utilized. The sensors operate in X-Band with 9.65 GHz. The dataset of 23 scenes was acquired in Staring Spotlight mode [13] between Septermber 2022 and September 2023. This acquisition mode enables the antenna to remain focused on a fixed ground target (e.g., a bridge) during the satellite overpass, resulting in an azimuth resolution of down to 25 cm. Furthermore, the 11-day repeat cycle of TerraSAR-X ensures consistent imaging geometry across all acquisitions, which is a critical requirement for PSI processing.

The PSI processing is done in the commercially available software ENVI® SARScape and follows a two-step inversion approach. In the first step, a system of linear equations Eq.(5) is solved to estimate the residual height (H_{res}) and linear deformation velocity (V) for each PS. In the second step, tropospheric phase contributions are estimated and removed to refine displacement time series. The final results, including elevation corrections and displacement values per acquisition date, are stored for analysis in a geospatial vector data format.

3 In-situ Data Integration and Validation

As part of the AutoSatBridge research project, the Sinzing Danube Bridge is being equipped with an advanced sensor system. The aim is to validate satellite-based measurements through precise in-situ monitoring to enable intelligent, continuous bridge assessment. The core component of the system is a hydrostatic leveling (hose gauge) system featuring six measurement points along the bridge and a central reference station located at pier 3. Five sensors are installed equidistant between pier 3 and 4. Another is located in the quarter point between pier 4 and 5. This system allows for highly accurate vertical displacement measurements with a precision of 0.1 mm and a range of 200 mm. Designed for harsh conditions, the system operates in a temperature range of –20 °C to +80 °C and meets at least IP67 protection standards. Due to the bridge's steel construction, the sensors must be mounted without drilling. A combination of magnets and adhesive was therefore chosen as the fastening method.

The hose gauge system is complemented by temperature sensors for monitoring the bridge girder's material temperature. These sensors are attached to the web of the bridge longitudinal beam in the connection area of the upper and lower flange. These sensors measure with an accuracy of 0.05 °C and cover a range of –50 °C to +100 °C. Additionally, a displacement sensor is installed to monitor bearing movements in bridges longitudinal direction, with a measurement range of ±100 mm and a precision of 0.01 mm. This sensor is attached to pillar 3, one span from the fixed point.

All sensors are connected to a central data acquisition system that manages data collection, temporary storage, and wireless transmission. The system is housed in a weather-resistant control cabinet (IP67) mounted on a steel frame, which also accommodates additional university-owned systems. A key component is the Industrial IoT Gateway, which supports standard communication protocols, preferably the publish–subscribe, machine-to-machine network protocol MQTT. Data transmission is carried out via LTE or 5G, with on-device buffering of at least 14 days to ensure continuity in case of mobile network outages.

To enable seamless integration into the University of the Bundeswehr Munich's data infrastructure, an IoT interface is configured for automated data transfer using MQTT. An MQTT broker in the AAS digital twin platform BBox receives the measurement data. Via the MQTT topic the data is assigned to the sensor data base.

4 Application to the Sinzing A3 Bridge

Initial results highlight the suitability of high resolution TerraSAR-X Staring Spotlight data for infrastructure monitoring. Figure 2 presents the horizontal distribution of persistent and distributed scatterers (PS and DS) identified within a TerraSAR-X datastack over the A3 motorway bridge. The TerraSAR-X data reveals clearly defined clusters aligned along the traffic lanes. No comparison with other data sources was conducted since the in-situ system was deployed in June 2025 two years after the Radar data was acquired.

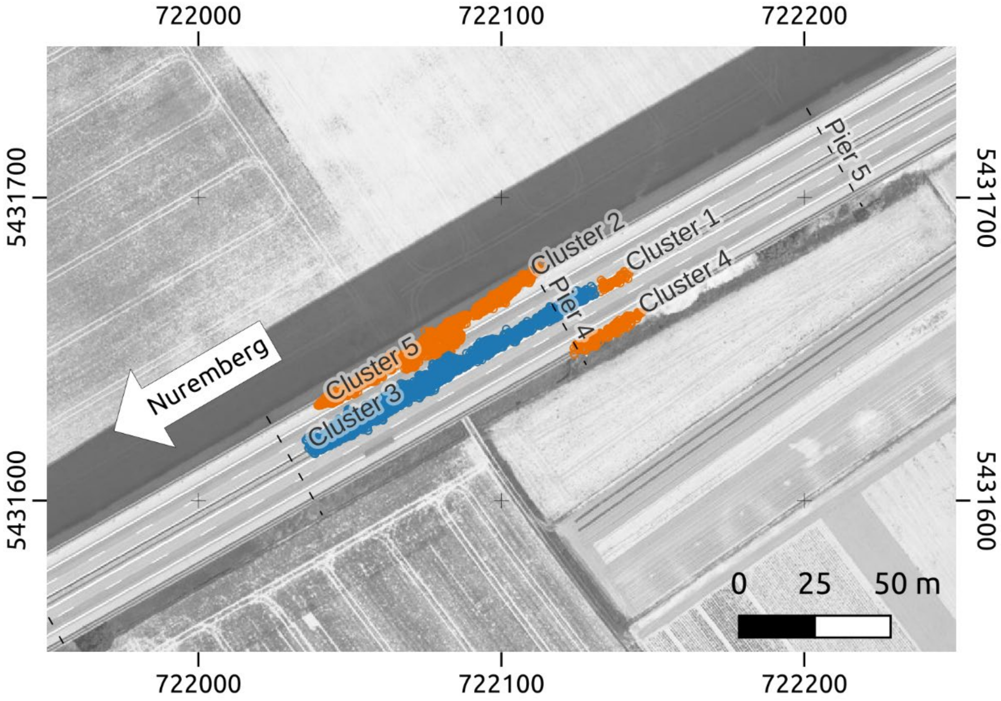

Figure 2: Distribution of PS and DS points on the bridge deck derived from 23 TerraSAR-X and TanDEM-X Staring Spotlight scenes acquired between September 2022 and September 2023

Focusing on the vertical displacements of clusters 3 in Figure 3, distinct temporal deformation patterns become apparent. Notably, a time-dependent deflection of the bridge span adjacent to pier 4 is observable. Around this pier, vertical displacements converge toward zero, as indicated by the vertical black dashed line in the displacement plots. These observations suggest the pier acts as a structural node around which dynamic loading effects manifest.

It is important to emphasize that the displayed measurements represent a combination of persistent and distributed scatterers. Backscattered signals may originate from geometric features such as corners, intersecting surfaces, or other reflective configurations that do not correspond to physically well-defined points.

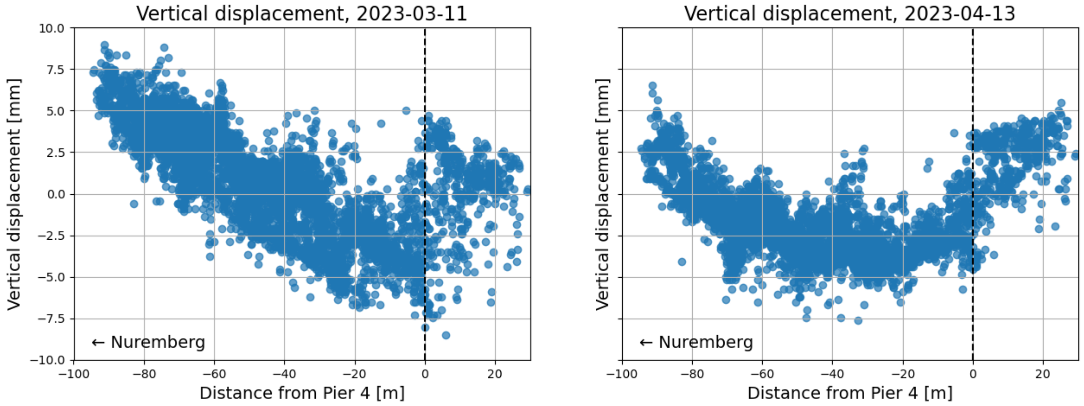

Figure 3: Vertical displacements exemplified for two dates on the cluster number 3. The dashed black line indicates the pier 4. Negative distances are towards Nuremberg

5 Towards AI-Powered Monitoring and the Digital Twin

The AI-based analysis described here is currently under development and will be implemented in the next phase of the AutoSatBridge project. This section outlines the planned methodology and integration strategy.

Locating the true origin of radar phase centres remains a key challenge in interpreting PSI results for structural health monitoring. To address this, the AutoSatBridge project aims to develop machine learning (ML) methods for the semantic attribution of persistent and distributed scatterers to specific bridge components. This will enable the derivation of deformation patterns at the element level, supporting more actionable infrastructure diagnostics.

Once attributed, the deformation histories of grouped scatterers will be fused to create robust, component-specific signals. These will be integrated into a digital twin using the Asset Administration Shell (AAS) framework. The digital twin will function as a central, structured representation of the bridge, incorporating EO-based displacement data alongside sensor measurements and BIM-derived geometry. This fusion supports real-time condition monitoring, anomaly detection, and long-term infrastructure lifecycle management.

The idea of a digital twin comes from the aerospace industry. The potential increase in productivity was soon recognized by the manufacturing and automotive industries, and the digital twin is one of the drivers of digitalization in Industry 4.0 [14]. One approach to implementing this digital twin is the AAS developed by Platform Industrie 4.0. It was used to create the virtual replication of a product, life cycle or process [14]. The advantage of this is that both static and dynamic data can be processed. One of these frameworks (BaSyx) was reinterpreted into an application for the life cycle management of bridge structures. It maps the planning, construction, operation and dismantling of a structure. The resulting software solution BBox is developed and maintained at the institute for structural engineering at the University of the Bundeswehr Munich. It offers the import, storage, visualization, processing and exchange of dynamic and static data in all directions [15]. An available database - the data is available in an InfluxDB-based solution - is essential for the development of ML algorithms in particular. Subsequently, developed models can be added back to the AAS as virtual sensors, allowing real-time evaluations to be carried out and visualized.

6 Conclusion and Outlook

The AutoSatBridge project demonstrates the feasibility and value of integrating high-resolution Earth observation, persistent scatterer interferometry, and artificial intelligence for scalable structural health monitoring of bridges. Initial results from the A3 Sinzing Bridge highlight the ability of TerraSAR-X data to reveal detailed deformation patterns, while the integration of in-situ sensors supports robust validation and calibration of EO-derived signals. Ongoing efforts focus on refining machine learning models for scatterer attribution and embedding results into a digital twin using the Asset Administration Shell. These developments not only enhance operational readiness and diagnostic precision but also contribute to the sustainable management of infrastructure in alignment with national and EU-level goals such as the SDGs and the European Green Deal.

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