Exploring Problems and Prospective of Satellite Interferometric Data for the Seismic Structural Health Monitoring of Existing Buildings and Architectural Heritage

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ABSTRACT: Satellite interferometric data represent a promising source of information for the Structural Health Monitoring (SHM) of the existing built environment. This is especially true because they show differential temporal-spatial displacements of remotely monitored points, which can be easily interpreted with a visual inspection of their time-histories for different locations defined a priori. However, the interferometric information is commonly referred to extended territories (at the scale of city or region), thus several problems arise in the implementation of automatic SHM techniques for the damage detection, localization, and assessment of the built environment at a point level (scale of the building or lower).
Despite a long list of challenges, interferometric data have also the potential to become a useful source to assess the health of a structure, especially for helping in define structural early warning methodologies. For this reason, in the paper, the authors summarize the main challenges in the use of satellite interferometric data for civil SHM, and rather than proposing remedial actions, try to critically analyze the challenges and perspectives for future applications.

KEY WORDS: Structural Health Monitoring, Remote Sensing, Satellite Data, SBAS-DInSAR, Line Of Sight, ReLUIS, Dynamic monitoring.

1 INTRODUCTION

In recent years, catastrophic events have increasingly highlighted the fragility of the infrastructures, buildings, and architectural heritage structures. More in general, entire urban areas have proved to be particularly vulnerable to natural phenomena caused by climate change, such as floods and landslides, but also by exceptional events such as earthquakes. This can certainly be attributed to the exceptional nature of the events; however, very often, also a lack of- or inadequate maintenances contributed to worsening the occurrence.

From this arises the need to find new monitoring techniques and technologies capable of providing data continuously and systematically, and with reduced costs. Among these new technologies, the possibility of using data gathered by constellations of artificial satellites, which for years have collected data of various nature regarding the earth's surface, is becoming increasingly interesting.

Satellite data are born for different purposes and far from civil Structural Health Monitoring (SHM). The potential of the employment of satellite data for purposes different than environmental monitoring was highlighted by [1] and has been applied by [2] for monitoring urban growth.

The employment of these data for SHM is, instead, extremely recent. In this regard, some satellites are aided with a technology called *Synthetic Aperture Radar* (SAR). The concept of SAR [3] indicates, more specifically, a satellite radar acquisition technique/technology that exploits the synthesis of an antenna with a kilometric aperture. This virtual antenna is simulated by acquisitions made on the same area, observed at different times and positions by the same satellite.

Among the various SAR techniques, the one called *Interferometric* SAR (InSAR) [4] is characterized by the fact that SAR images of an area (representing for example the phase difference between satellite and target on the ground for each observed point, or more simply the *satellite-target phase*) are compared over time within a *baseline time*. The representation of the differences in the *satellite-target phases* (differences made between different temporal acquisitions of the same area), provides the interferogram, which, therefore, represents the comparison of multiple SAR images in terms of the *satellite-target phase* difference. Thus, an InSAR interferogram is built when in the evaluation of the phase difference between two instants in time, various components of the phase, such as the angle of incidence component and the topographic component, are considered. Instead, a differential interferogram is obtained from the *Differential Interferometry* SAR (DInSAR) [5] when in the representation, only the pure displacement component of the differential *satellite-target phases* is depicted. The DInSAR technique specializes, compared to the InSAR technique for estimating coherent target displacements, even if the two techniques are closely related.

The DInSAR information allow the estimate, with processing algorithms such as the *Small BAseline Subset*-DInSAR (SBAS-DInSAR) [6], [7], of displacements of the order of centimeters and millimeters along the Line Of Sight (LOS). From this point forward, we will refer to interferometric satellite data, or satellite data, or interferometric data as data coming from satellites equipped with SAR.

Some first application of satellite interferometric data has been implemented to monitor aggregated buildings in urban areas [8], [9], [10], to analyze the effects of land subsidence in built environments [8], [11], [12], and then for detecting anomalies in single structures [13], or infrastructures [14], [15].

Despite these first applications, some challenges are still open and need to be explained, especially as regards the integration of interferometric satellite data with the dynamic monitoring techniques commonly used by who work in the SHM of the built environment and the seismic monitoring of structures. With this paper, the authors want to critically analyze some of these challenges encountered in the usage of satellite interferometric data within the first two years of the ReLUIS-DPC 2019-2021 project (www.reluis.it), *WP6 Monitoriaggio e Dati Satellitari* (in Italian).

The overall main challenge consists in adopting data processed with techniques derived for the analysis of vast territories, for the civil SHM of punctual systems (e.g., civil structures). The difficulties subsist for two main reasons:

- *Technological discrepancy*: standard civil SHM techniques have not been thought to be used with such type of data.
- *Observation scale*: satellite data, which were used in the past (and are still used nowadays) for the monitoring of the environment and earth derived phenomena at large scales of study, find difficulties in observing the physics of civil structures, which also require the study and representation of "small-scale phenomena".

The aforementioned problems will probably be solved with the forthcoming technological advancement in Remote Sensing and SHM. However, without a clear picture of the current weaknesses in the synergistic use of these two disciplines some aspects could be overlooked, slowing down the solution of the existing problems. Thus, the main objective and importance of the study lies in helping to bridge the existing gap between civil SHM techniques, built environment and satellite interferometric data (Figure 1).

This is pursued by recalling the basic rules of civil SHM and the standard approaches used to identify the damage (Section 2). Then, the main current challenges in the analysis and use of satellite interferometric data for civil SHM are outlined and discussed (Section 3). The paper flows down with a discussion of some perspectives, highlighting the potential benefits of the synergistic use of satellite interferometric data and civil SHM techniques (Section 4). Finally, some conclusions are drawn (Section 5).

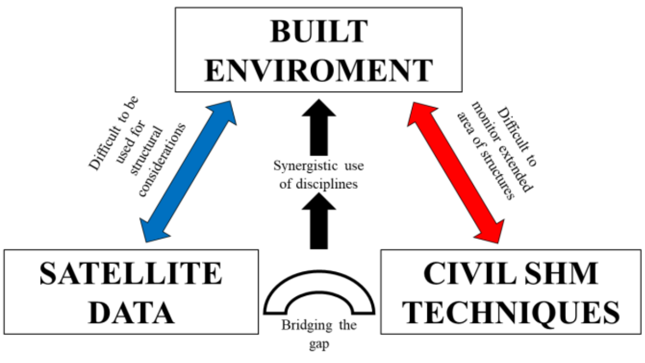

Figure 1. Gap between disciplines.

2 STANDARD APPROACHES IN CIVIL SHM

The SHM [16] is nowadays an active discipline in several applications and research fields. It can be defined as the *process of implementing a damage detection strategy for engineering infrastructure* [17]. The effort of the research on this topic brought, in 2007, to the definition of several *Axioms* [18], which instead to define an unequivocal sentence, are used as a starting point, like guidance, in research. Thus, they are assumed to be true since they are supported by a strong evidence that is shared by an entire community. These axioms can be summarized, for the SHM discipline, as follow (see [18] and [19] for more details):

- Axiom I: *All materials have inherent flaws or defects*.
- Axiom II: *The assessment of damage requires a comparison between two system states*.
- Axiom III: *Identifying the existence and location of damage can be done in an unsupervised learning mode, but identifying the type of damage present and the damage severity can generally only be done in a supervised learning mode*.
- Axiom IVa: *Sensors cannot measure damage. Feature extraction through signal processing and statistical classification is necessary to convert sensor data into damage information*.
- Axiom IVb: *Without intelligent feature extraction, the more sensitive a measurement is to damage, the more sensitive it is to changing operational and environmental conditions*.
- Axiom V: *The length- and time-scales associated with damage initiation and evolution dictate the required properties of the SHM sensing system*.
- Axiom VI: *There is a trade-off between the sensitivity to damage of an algorithm and its noise rejection capability*.
- Axiom VII: *The size of damage that can be detected from changes in system dynamics is inversely proportional to the frequency range of excitation*.

A standard approach in civil SHM should, ideally, follow these *basic truths*.

In addition to the previous axioms, one is emerging in the last years (starting from 2010) as a conjecture. This conjecture would state that the *damage increases the complexity of a system*, leaving, in this definition, the term *complexity* as a concept (i.e., not precisely defined), [20]. Later, the concept of complexity was better specified for applications in SHM [21], also giving some methods to measure it, for example, through the use of different entropy definitions in information theory [22].

Following Axiom IVa, to make considerations on the health of a system, some features belonging to the same should be extracted and analyzed implementing either black (non-physical based), gray (semi-physical based), or white (physical based) approaches. These features are extracted from the processing of observable quantities measured thanks to dedicated monitoring systems. An observable quantity coming from a system is commonly referred to as *sensing structural response*, and in civil SHM, especially for the seismic discipline, it can be an acceleration, displacement, strain, etc. In this context, satellite interferometric data are entering the discipline of civil SHM as a new sensing structural response. For this reason, the paper aims to highlight some of the emerging challenges in the use of this new sensing structural response to extract structural features for damage identification. Generally, SHM is aimed, but not limited to, the identification of the damage. Damages can be defined as *changes introduced into a system that adversely affects its current or future performance* [17], while for "changes introduced into a system" is intended a *change in material, or geometric properties, changes in boundary conditions or in the system connectivity properties* [17]. The damage identification can be then classified following 4 levels of implementation difficulty [23]:

- Level 1: Detection of the existence of damage.
- Level 2: Geometric localization of damage.
- Level 3: Severity assessment of damage.
- Level 4: Prediction of the remaining structural life.

where, in level 3, with the term *severity* is intended the quantification of the extension and/or the magnitude of the damage, which in principle, to make physical considerations on the health of a system, should always be associated with a *type* or *typology*. By looking at the previous levels, it is easy to conclude that while the first 3 concern the diagnosis phase, the last one deals with the more complicated prognosis stage.

SHM should not be confused with the *condition assessment*. The latter is, in fact, more related to intensive short-term campaigns such as controlled load testing, dynamic testing, etc., while the first is commonly associated with continuous automated measurements in time, ranging from days to the entire lifetime of a system [24]. If in SHM satellite interferometric data are emerging as a new sensing structural response, in the field of Condition Assessment they could be advantageously used for anomaly/novelty detection [25], [26] for early warning, thus helping to answer the question: *When a condition assessment (e.g., visual inspection, testing campaigns, etc.) should be performed, out of the ordinary maintenance tasks?*

Figure 2 reports the rate of occurrence of the *Ngrams* "Structural Health Monitoring" and "Condition Assessment" in the Google Books database for documents dated from 1950 to 2019.

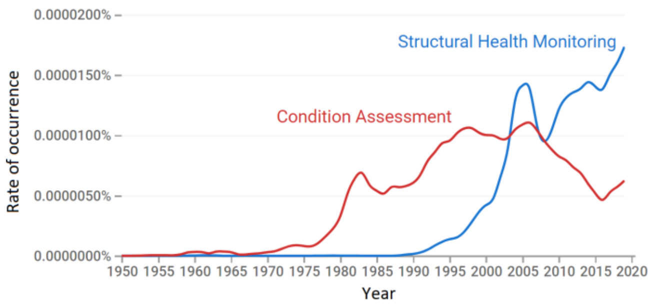

Figure 2. Rate of occurrence of the 3grams "Structural Health Monitoring" and the 2grams "Condition Assessment" in the Google Books database. The graph shows curves smoothed with a moving average (over three years) of the rate of occurrence in each year, (https://books.google.com/ngrams/graph?content=Structural+Health+Monitoring%2C+Condition+Assessment&year_start=1950&year_end=2019&corpus=26&smoothing=1&case_insensitive=true, 2021, January 6th).

To conclude, it is worth state that axioms, as previously specified, are not unequivocal sentences, and thus in principle, one can choose to follow or not follow them. In the proceeding of this paper, the authors will arbitrarily suppose the previous axioms as a basic truth.

3 CHALLENGES IN THE USE OF SATELLITE INTERFEROMETRIC DATA FOR CIVIL SHM

Axiom I and II state, respectively, that all materials and, from a broad view, structures are damaged and that the assessment (starting from level 1), requires a comparison between 2 system states. The two states are the initial and the final, possibly damaged, state.

Axiom III defines the need for "labels" (data are available from both the initial and damaged state of the system) to train a specific method of damage identification in case the assessment would face the 3rd level. The first two levels of damage identification, instead, can be commonly faced without information on the damaged state of the system, although in this case, the identification is often more complicated. From this, it is possible to conclude that damage can be detected and located thanks to satellite interferometric data just in the time windows of observation, while the identification of the type and the assessment of its severity would not always be possible with data falling in this time window. To clarify the concept, the damage that occurred at the beginning or at the end of the time of observation could not be assessed in its typology and severity because there would not be enough data before and after the occurrence of the damage, respectively, to deal with the 3rd level of damage identification. The length of signals derived from satellite acquisitions and processing should be thus designed in order to include three parts: (i) a starting part where just the first two levels of damage identification can be applied; (ii) a useful part where all the levels of damage identification can be reached; (iii) an ending part analogous to the starting one. In addition, although the missing information in time can complicate the achievement of the 3rd level of damage identification, more important, a poor spatial resolution of data may not enable to calibrate a model at all (i.e., supervised learning), and without a calibrated model it is quite hard to judge about damage type or to quantify its severity.

Axiom IVa requires the need to process the sensing structural response and extract from it one or more features. Hence, in theory, satellite data showing structural displacement responses (or differential displacements, projections, etc.) should be processed before estimating damage indicators, which in turn should refer to extracted features instead of structural sensing responses.

Axiom IVb defines a tendency to the indeterminacy of damage with respect to a specific measurement because of the existence of operational and environmental variations in it. The uncertainty can be reduced with intelligent feature extraction; thus, this axiom (IVb) is closely linked to the previous one (IVa) as it reiterates the need to extract intelligent features from satellite interferometric data instead of directly using the sensing structural response. Given the existence of uncertainty, the axiom intrinsically recalls the need to carry out statistical and/or probabilistic studies. In addition, a study of the operational and environmental variations affecting satellite data is required.

Axiom VI states that regardless of the method used, the minimum detectable damage threshold increases as the Signal to Noise Ratio (SNR) in the structural sensing response used for SHM decreases. This defines a limit of detectability (and thus a limit on all the other levels of damage identification) that should be studied for satellite interferometric data because of their slightly different nature from data commonly used in civil SHM. The latter, in fact, are recorded with systems specially designed for civil structures, which generate, in general, data with high SNR concentrated in specific frequency ranges of the response, making the (partial) noise rejection easier with the use of dedicated filters or de-noising techniques. For satellite derived data, instead, the amount of SNR over the frequency bandwidth of measurement is not something straightforward to define (at least at this stage of the research), and the same concept of noise should be carefully understood.

Finally, axiom V and VII are directly related to the (length-time-) scale of damage, and thus, to the observation scale. Based on the characteristics of what is being observed (satellite interferometric data in the proceeding of this article, i.e., Line of Sight Displacements – LOSDs or derived quantities), some type of damage may not be detectable. This is particularly true if the satellite sensing system is not optimized for civil SHM purposes. Then, axiom VII introduces the role of excitation, stating that extensive or severe damages are detectable with a low frequency range of excitation. On the other hand, small damages are detectable with a high frequency range of excitation. In other words, if the frequencies of the excitation increase, the damage sensitivity increases. This last axiom calls for an in-depth analysis of the "frequency range" and the meaning of "excitation" in satellite data used for civil SHM.

Based on the previous statements, it is possible to draw some considerations on the use of satellite interferometric data for civil SHM.

3.1 Challenge 1

The first challenge concerns the amount of data that need to be processed, approximately in the order of millions of points for an urban area (see, for example, Figure 3). Very often, still today, in civil SHM, the verification of an algorithm outcome and the validation of its specifications, in addition to automatic verification and validation methods, is carried out manually, visualizing the result of processing. This is necessary because of the very complex pattern that a structural signal can take. If satellite data wants to be used for structural analyses on extended areas (i.e., a huge number of structures to be analyzed), and not only for analyzing singular isolated structures, very robust algorithms should be preferred since automatic techniques must be employed, and no manual verification can be performed.

A clarifying example is the problem of model fitting. In this case, the hyperparameters of an algorithm used to estimate model parameters could be optimal to analyze some agglomerate of structures. However, they could fail to represent the remaining (e.g., producing overfitting or not catching at all the best model parameters). This is mainly due to the heterogeneity of systems analyzed on a large territorial scale. Thus, here the Axiom IVb plays an important role, especially for what concerns the "intelligent features extraction", which in the last years is becoming synonymous of the use of methods belonging to the artificial intelligence, probabilistic (e.g., Bayesian probability), and machine learning disciplines.

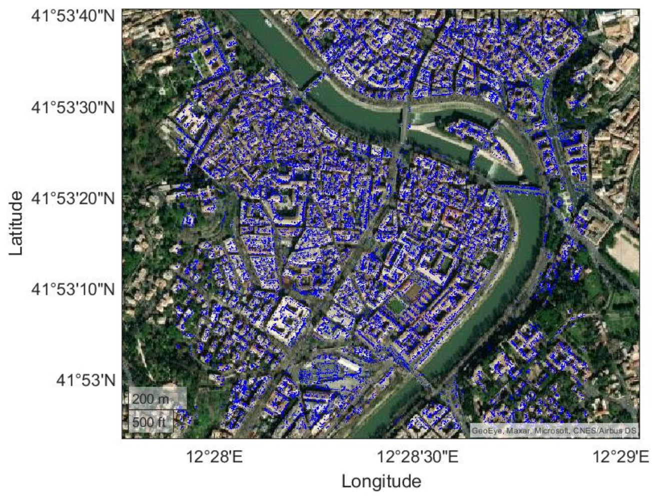

Figure 3. Example of map showing the numerosity of points obtained by satellite interferometry over a neighborhood of the urban area of Rome (Italy).

3.2 Challenge 2

From Challenge 1 directly derives this challenge. Discriminating structural typologies thanks to the use of satellite data would favor the verification and validation processes. For example, calibrating the hyperparameters of the algorithms on sets of structures having similar characteristics would reduce many difficulties due to the heterogeneity of the systems over a vast territory. This problem, therefore, calls for the implementation of classification techniques. The classification is also useful for discriminating the effect of operational and environmental conditions on structures since structures with different characteristics behave (albeit following a common baseline) slightly differently if subjected to these variations (e.g., steel and masonry structures subjected to temperature variations).

3.3 Challenge 3

The classification should be implemented to deal with another challenge. Satellite interferometric data are thought to capture points over a large area, and for this reason, some measured points can fall out of structural systems (e.g., road signs, trees, etc.). Discriminating structural points from non-structural is also essential for the first level of damage identification and in the case of detection of anomalies in signals. Anomalies in signals not originating from structural systems would, in fact, increase the uncertainty of the analyzes, not only to perform SHM but also to suggest tasks of condition assessment. Figure 4 and Figure 5, for example, show the Line Of Sight Displacement (LOSD) obtained from satellite interferometry for a structural (Point A) and a non-structural (Point B) system.

Figure 4. Location of the points associated to the LOSD reported in Figure 5, (https://www.google.it/maps/@41.8876911,12.4683761,61a,35y,291.8h,55.35t/data=!3m1!1e3).

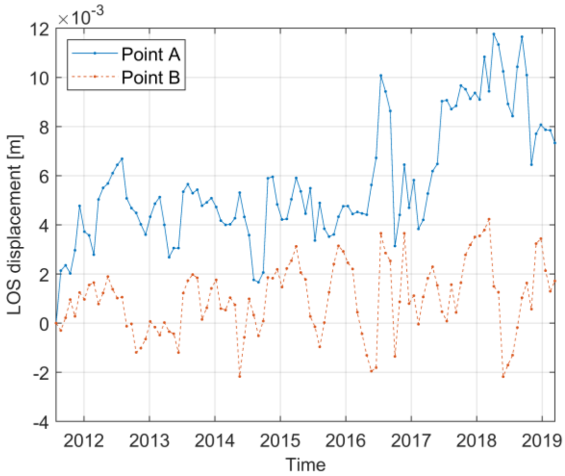

Figure 5. Line Of Sight (LOS) displacement obtained by satellite interferometry and associated to the points depicted in Figure 4; Point A – latitude: 41.88781, longitude: 12.46782; Point B – latitude: 41.88795, longitude: 12.46738.

3.4 *Challenge 4*

Structural sensing responses obtained from satellites are the results of processing algorithms and thus are prone to contain errors. The recognition of these processing artifacts (e.g., ghost points), like in Challenge 3, would help to reduce the uncertainty of the analyzes of SHM and Condition Assessment on a territorial scale.

3.5 *Challenge 5*

In civil SHM, the observed data are commonly sampled at a constant time (i.e., coefficient of variation of the sampling time approaching to zero) and missing points occurring in time are commonly low with respect to the number of total recorded points in a signal. This means that interpolation techniques can be advantageously used to remedy the lack of information. For satellite recorded data, the sampling time of a measure is related to the revisiting time of satellites and the numerosity of the constellation. The current revisiting time, however, generates signals with large sampling time with respect to that one generated by a common in-situ civil SHM sensing system. Then, when missing points occur, they generate a very large gap in signals, producing non-uniformly sampled measures for which resampling and advanced interpolation techniques need to be implemented (see Figure 6 for clarity). However, when data contain large gaps, also the implementation of advanced interpolation techniques may result inadequately for solving the issue.

More precisely, the interpolation problem depends on mainly 4 factors: (i) the frequency content of the signal; (ii) the sampling frequency of the signal; (iii) the time length of the signal; (iv) the number of samples of a signal. These factors inspired the following challenges.

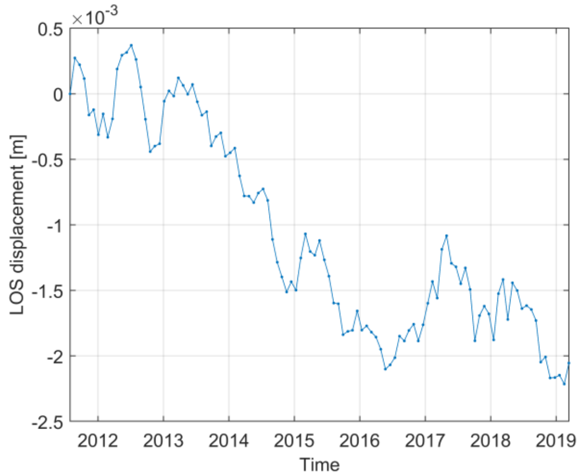

Figure 6. Average Line Of Sight (LOS) displacement over the area of Rome (Italy).

3.6 *Challenge 6*

The frequency content of LOSD and its derived quantities clearly depends on the system to which they belong and the nature of the perturbations that act on that system. The perturbations that can act on a system are countless. They can regard:

- Rare events such as earthquakes, floods, hurricanes, fires, catastrophic collapse of subsoil, etc.
- Periodic events such as rains, snowfall, temperatures variations, relative humidity and atmospheric pressure variations, changing in soil conditions due to environmental factors, etc.
- Persistent events such as subsidence, wind, vehicular traffic, and other anthropogenic vibrations, effect of tidal motions and other very low frequency phenomena that act on the earth, etc.

All these perturbations can act simultaneously or not and define the sources of excitation of monitored civil structures. However, from a monitoring point of view, it is often unfeasible (or very difficult) to include all the previous phenomena in the measurements because data are sampled, and what it is possible to observe is generally limited to a useful “frequency range”. It is worth mentioning that phenomena out of this frequency range continue to exist, and their presence, in some cases, can still be perceived (think of very low frequency effects) even if not fully understood with single acquisitions. For example, for satellite interferometric data used in the ReLUIS-DPC 2019-2021 project (www.reluis.it), this frequency window ranges from 3.5e-9 Hz to approximately 2.5e-7 Hz (time periodicity between about 30-40 days and 8-9 years). Thus, the challenge is to understand how perturbations acting on these frequency ranges (including operational and environmental conditions) can affect remotely monitored civil structures and understand if perturbations out of the frequency range can be indirectly perceived with satellite interferometric data. In addition, concerning environmental perturbations, it is questionable how to solve the problem of the different spatial resolution of LOSD and environmental data since environmental data acquired in positions different from those used to measure LOSD may increase the uncertainty of future analyzes. Figure 7 and Figure 8 show, respectively, the temperature history acquired by the ROMA station (regional ARSIAL Lazio network) and the LOSD obtained from satellite interferometry in (approximately) the same point. The temperature history has been resampled to the average sampling time of LOSD, while the LOSD history has been resampled to its average sampling time and interpolated with autoregressive models [27].

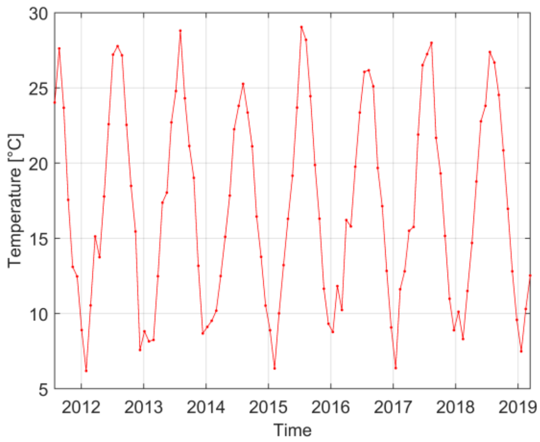

Figure 7. Temperature in Rome; latitude: 41.920555, longitude: 12.523626, (http://193.206.192.214/servertsutm/serietemporali100.php).

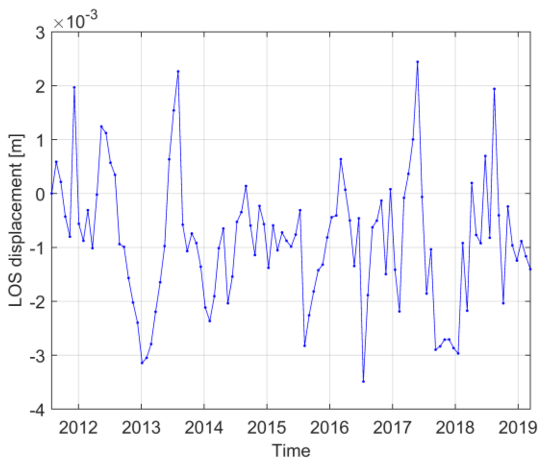

Figure 8. Example of Line Of Sight (LOS) displacement obtained by satellite interferometry; latitude: 41.920560, longitude: 12.523500.

Clearly, this is a very challenging task, also because the frequency range commonly used by civil SHM sensing systems (e.g., in-situ accelerometers network) falls in the order of hundreds of Hertz. This because the natural frequencies associated with civil structures are in the order of tenths, units, or tens of Hertz, depending on the structure. Therefore, the maximum frequency commonly perceived (half of the sampling frequency) by an operator working with standard civil SHM sensing systems is about 7 orders of magnitude higher than that one perceived by working with satellite interferometric data. However, it is to be hoped that in the not-too-distant future, these problems can be, if not resolved, simplified by technological progress. In doing this, it will be essential to understand if there is a lower physical limit to the revisiting time of a point monitored by satellite (e.g., a trade-off between sampling time and the number of missing points). In any case, the reduction of the revisiting time would allow analyzing an ever-wider band of frequencies. Currently, this band contemplates very low frequencies. In these conditions, considering the natural frequencies of civil structures (very high with respect to the sampling frequency of satellite sensing system), what it is possible to observe are signals mostly driven by perturbations falling in these very low frequencies, and probably damages mostly associated with very low and/or extremely severe phenomena (e.g., subsidence, fatigues, sinkhole, etc.). Figure 9 and Figure 10 show the modulus of the Fourier Transform for temperature, relative humidity, and rain data resampled to the average sampling time (about 22 days) of data obtained from satellite interferometry (i.e., LOSDs).

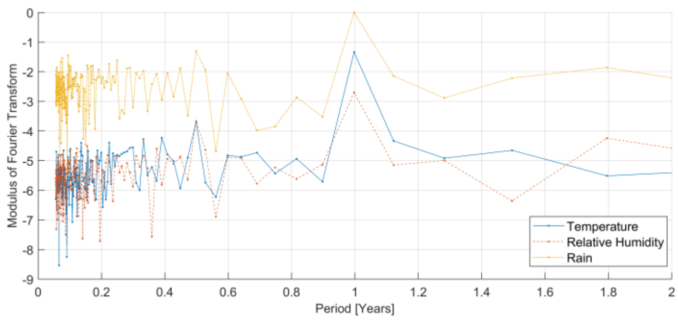

Figure 9. Modulus of the Fourier Transform (between 0 and 2 years of period) of temperature, relative humidity, and rain in Rome; latitude: 41.920555, longitude: 12.523626.

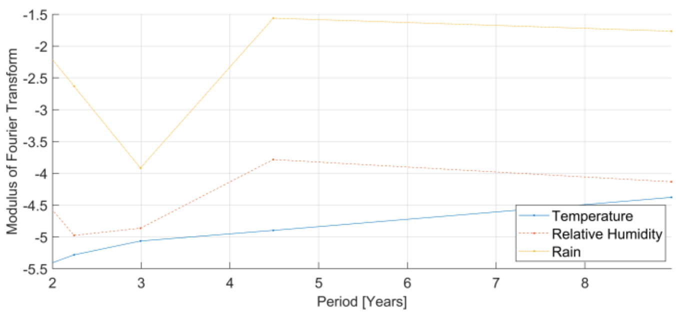

Figure 10. Modulus of the Fourier Transform (between 2 and 9 years of period) of temperature, relative humidity, and rain in Rome; latitude: 41.920555, longitude: 12.523626.

3.7 Challenge 7

The sampling frequency (object of Challenge 6) defines the upper boundary of the frequency range of LOSD data. This challenge, instead, focuses on the lower boundary, which is dictated by the frequency resolution of data.

The frequency resolution is inversely proportional to the time length of the signal, meaning that for LOSD data (with time lengths of some years for the specific case of the article), it is possible to obtain a better resolution than those commonly used with standard dynamic civil SHM sensing systems. However, this is possible because of the lower sampling frequency. In fact, also standard dynamic civil SHM sensing systems can reach extremely fine frequency resolutions, as it only depends by the time length of the acquisitions. Low values of frequency resolutions means that it is possible to perceive low frequency (or long period) phenomena.

Commonly, for data coming from standard dynamic civil SHM sensing systems, the obtained frequency resolutions are in the order of hundredths or thousandths of Hertz. The time lengths of the signals, instead, range approximately from tens of seconds to tens of minutes. It is clear now that the limit to analyze very long signals with very high sampling frequency is dictated by the computational time. In the next future, processing signals with billions of time samples will probably be possible. However, for the time being, to benefit of satellites interferometric data, some considerations on the characteristics of the signals derived from satellite can be drawn.

If the main scope (but not the only one) of satellite data used for civil SHM is to catch low frequency phenomena compared to phenomena commonly observed with dynamic civil SHM in-situ sensing systems, the first limit that can be imposed is on the sampling frequency or sampling time. This depends on the perturbations that one want to catch with these data. It is known in civil SHM that environmental factors modify the structural response of the built environment. Sensible variations, however, are perceived over long periods (e.g., hours or days). Thus, a compromise to have signals with not too many samples and able to catch hourly variations could be to choose a sampling time lower than half of a day (corresponding to a sampling frequency higher than 2e-5 Hz).

Then, the number of time samples should be enough to obtain non-grainy data (see Figure 9 and Figure 10 for a grainy signal). In this, data coming from standard dynamic civil SHM in-situ sensing systems can help. In fact, for these data, the number of time samples commonly ranges from 2000 to 200000 or more. The number of samples is just the product between the time length of a signal and its sampling frequency.

For example, supposing that data coming from satellites should have the same number of time samples of a signal coming from in-situ SHM systems, it is possible to obtain an estimate of the time length of data coming from satellites. Supposing a sampling time of 4 hours (i.e., a sampling frequency of about 7e-5 Hz) and 20000 samples, is easy to get a time length of approximately 9-10 years. Table 1 reports some common characteristics of signals coming from dynamic in-situ and satellite sensing systems.

Table 1. Signal characteristics.

Data from SHM system	Sampling time [s]	Time length [s]	Number of samples [-]
Dynamic in-situ	0.001-0.02	20-1000	2000-20000
Satellite interferometric	Thousands	Millions	Hundreds

3.8 Other challenges

Other challenges can regard the study of the meaning of noise for satellite interferometric data, especially for what concerns the low frequency behaviors, which could be associated with meaningful information instead of baseline noise.

Then, a questionable topic will be the research of structural features that can be extracted from LOSD (and their derived quantities) and used for civil SHM, especially because the natural frequencies of the monitored structures are much higher than the frequency range spanned by satellite interferometric data. Then, the definition of right thresholds for these features represents another challenge. Other questions that call for an answer are instead listed hereinafter:

- In standard civil SHM in-situ sensing systems, the location of each acquisition is stable in time and space. For satellite interferometric data, this fact is not generally true. How to deal with this problem?
- How to integrate outcomes of in-situ SHM with the outcomes of remote SHM?
- and so on.

4 PERSPECTIVES OF USE OF SATELLITE INTERFEROMETRIC DATA FOR CIVIL SHM

A lot of challenges in the civil SHM with satellite interferometric data have been outlined. However, despite the long list of challenges, this new data, representing a structural sensing response, have also several potentials applications.

Firstly, LOSD could be coupled to environmental data, helping to understand how these perturbations affect the response of civil structures in the long period, especially for what concern the alterations of soil characteristics, which represents a boundary condition for civil systems. Similarly, LOSD can be used to infer black- or grey-box models of structures, becoming potentially useful in helping vulnerability studies or in the understanding of the soil-structure interactions and the behavior of the soil surrounding a building or an architectural heritage structure.

Because of the continuous and permanent availability on a large area of satellite interferometric data, they may be used, in the future, to understand how structures behave before and after rare and catastrophic events and to understand if it is possible to extrapolate some common patterns. Then, the continuity of these data on a large scale would hopefully allow the monitoring of slow events in order to prevent catastrophic collapses.

If in the future automatic methods of classification would allow reaching a good degree of accuracy and reliability, satellite interferometric data could be used to create a database of structures having similar structural characteristics. Then, to approach in a more straightforward way to the 3rd level of damage identification with satellite interferometric data, in the near future, a database of damaged structures indicating the time occurrence, the type, and the characteristic of damage should be drawn up by the competent authorities.

Finally, since the monitoring with satellite data has the great advantage to observe the behavior of structures on vast territories, the interconnection of the information between structures thanks to advanced intelligent techniques could help to boost the growth of smart cities by generating, for example, intelligent structures capable of providing mutual recommendations on their structural state in order to self-alert in the event of anomalies.

5 CONCLUSIONS

Satellite interferometric data, and more specifically LOSDs, can represent a new promising structural sensing response of civil structures, potentially providing “low-cost” continuous information on a large number of structures. Several challenges need to be faced in order to solve critical existing problems before applying these data for civil SHM with reliability. The importance of this study, therefore, resides in providing a starting point of study for those who want to deal with civil SHM and satellite interferometric data. Dealing with the challenges and the future perspectives outlined in the paper would also help in the definition of protocols for the use of satellite interferometric data for civil SHM.

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