Design and Application of a Statistical Learning Methodology to Remove Temperature Effect on Static Signals for Bridge Structural Health Monitoring

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ABSTRACT

Infrastructures are essential for the development and flourishing of countries; in this context, bridges play an irreplaceable role as links for goods and people. Nowadays, their structural integrity is threatened by ageing and increased traffic loads: according to the American Society of Civil Engineering, 42% of US bridges are at least 50 years old. The extension of the problem requires the application of techniques for resource prioritization and effective interventions. Structural health monitoring (SHM) has emerged as a promising quantitative tool for ensuring infrastructural network resilience and optimizing maintenance. In particular, damage detection is crucial in preventing catastrophic failures and minimizing repair costs. However, the influence of exogenous factors on sensor signals often complicates the identification of damage, since they might hide the insurgence of structural anomalies. The problem is especially critical when dealing with early-stage damage, characterized by a small extension. Among such external variables, temperature, in particular, significantly disturbs SHM both on seasonal and daily levels. The latter is further exacerbated by the thermal inertia of bridges, which renders the structural behavior highly non-linear with respect to temperature and solar radiation. This study proposes a novel approach to enhance the identification capability of structural health monitoring systems by removing the temperature effect on static measures thanks to a statistical learning algorithm. In particular, signals from inclinometers and LVDTs collected for a year are considered for temperature influence removal. The method works according to a two-step process described in Figure 1. First, the seasonal dependence is removed; then, the daily influence of temperature and solar radiation is treated by exploiting a machine learning algorithm able to estimate the structural response delay caused by thermal inertia. The methodology herein presented is applied and tested on two railway bridges: a Warren truss steel bridge and a CACP bridge with simply-supported spans. In both case studies, the variability of the measured signals associated with temperature reduced substantially. Indeed, the correlation coefficients dropped close to zero, and the standard deviation of signals diminished by 80% on average. Moreover, the different structural characteristics of the two test cases proved the methodology effective and versatile, suitable for different typologies of bridges. The algorithm described in this work enhances the damage detection power of structural health monitoring systems and fits with the idea of SHM deployment on a larger scale, given its successful application to diverse structural archetypes.

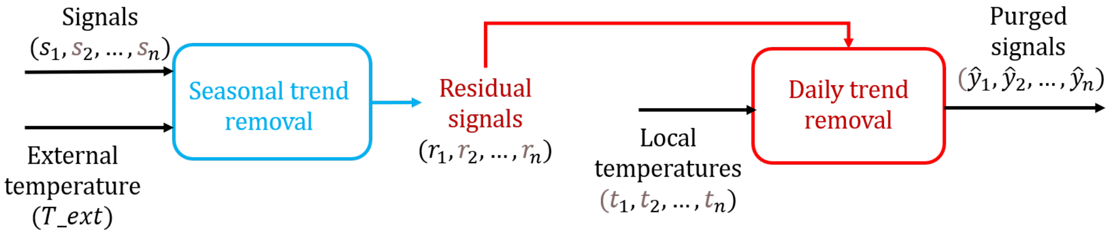

Figure 1. Schematic description of the methodology for removing the temperature influence on signals.

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INTRODUCTION

Bridges and viaducts play a crucial role in the functioning of rail and road infrastructural networks [1]. Numbers confirm land transportation as the primary vehicle of goods and people [2], thus essential to guarantee a prosperous economy and good social and cultural development in the long run [3]. Consequently, the correct maintenance of bridges should be a priority for each country's government. This issue is overbearingly coming upfront as infrastructural ageing [4], extraordinary climate events [5], and traffic volumes [6] increasingly threaten such structures. Structural health monitoring is emerging as a promising helping hand to provide quantitative and timely information supporting the decision-making process in matters of optimal maintenance. In particular, it is believed that such a diagnostic methodology could enable the transition to predictive maintenance, which consents to a more efficient allocation of resources and improves network availability. However, for this hypothesis to come true, it is necessary to demonstrate the SHM capability to identify anomalies and damages, better if in their early stage. Damage occurrence causes changes in a structure's physical and mechanical properties, leading to changes in static and dynamic behavior. Structural health monitoring aims to discover such phenomena by looking at data from sensors installed on the bridge. Unfortunately, damage is not the only reason why one might find variations in the measured signals. Operational and environmental factors, indeed, heavily influence the structural response ([7], [8]), to an extent that often overcomes the effect of possible damage [9]. Such a condition challenges the anomaly detection capability of structural health monitoring systems. Thus, researchers in the field have been focusing on developing signal-processing techniques that could effectively reduce the signal variability linked to non-structural variables. Among the latter, temperature represents a major concern for several reasons ([10], [11]). First, the temperature-induced variations are significant and not equal for bridges of different typologies. Also, the relationship is usually highly non-linear due to thermal inertia, which provokes a delay in the structural response with respect to the measured temperature. Ultimately, there is a problem linked to solar radiation, which induces a daily thermal cycle, often disregarded, whose magnitude can be comparable to the seasonal one, particularly during summer or spring, characterized by sunny days with intense solar radiation. The superimposition of such conditions makes it extremely complex to define a general analytical model to interpret the phenomenon, which is better suited for a data-driven study. This paper proposes a novel methodology based on statistical learning to remove temperature effects on static signals collected on bridges for monitoring purposes. The technique consists of a two-step process that separately treats seasonal and daily phenomena using external and local temperatures as independent variables. Conclusively, a successful application on two railway bridges of different typologies - a Warren truss steel bridge and a CACP bridge - is presented, considering measures from LVDTs and tiltmeters. The paper is structured as follows: (i) presentation of the case studies; (ii) methodology definition and explanation of the interpretative model and data sets; (iii) discussion of the results; (iv) conclusions and proposal for further developments.

THE CASE STUDIES

Figure 2. Photos of the railway bridges object of this study. On the left, the Warren truss bridge; on the right, the CACP bridge.

The methodology explained further has been applied to two railway bridges located in Italy: a Warren truss steel bridge and a CACP bridge (Figure 2). The first one was designed in 1946, and for each transit direction, the structure is composed of two spans about 60 m and 40 m long, respectively. The spans are simply supported, with hinges at the entrance and sliders at the exit, and are structurally decoupled except for the track system and the discontinuity pier. The CACP bridge features a modular hyperstatic structural scheme. Each module comprises two external piers connected to the deck through sliders, and two continuity inner piers which depict a π-shaped structure. The deck of each module is approximately 60 m long. The bridges are provided with permanent monitoring systems featuring different sensors, among which tilmeters and LVDTs are present. The positions of such transducers, object of this paper, on the two bridges, are reported in Figure 3. The installed monitoring systems allow also for environmental conditions tracking (e.g. temperature, solar radiation, etc.), useful to get information needed to then remove their effect on sensor measurements. The data of all the transducers considered in this paper are logged continuously at low frequency (1 Hz).

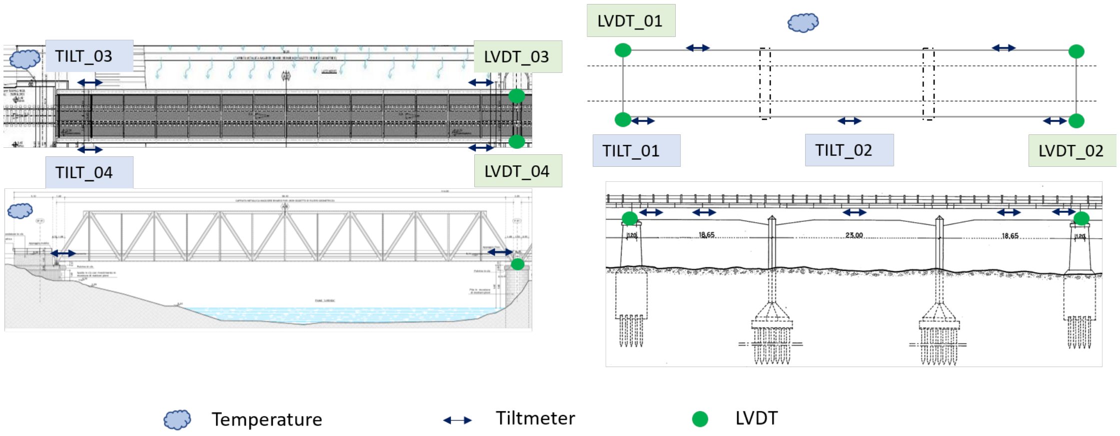

Figure 3. Schematic representation of the monitoring systems. On the left, the steel bridge monitoring system; on the right, the CACP bridge monitoring system. The eight sensors used in this study are labelled.

DATA, METHODOLOGY AND INTERPRETATIVE MODEL

This paper details a statistical learning methodology to remove temperature influence on static signals produced by tiltmeters and displacement transducers belonging to sensing systems for bridge structural health monitoring. The data involved in this study have been collected for one year on two bridges, presented in the previous section. For each structure, two tiltmeters and two LVDTs are taken into consideration. Also, the methodology needs information regarding the ambient temperature, measured through weather stations near the bridges, and local temperatures, acquired by the sensors themselves. Following the best practices in the field of statistical learning [12, 13], data are divided into a training set, used by the algorithm as a learning base, and a test set, on which its performance is assessed. Data splitting relies on randomly extracting the 10% of the samples and puts them aside for successive testing [14].

The training set feeds the algorithm according to a two-step methodology: first, the seasonal trend, also referred as macro-trend from further on, is removed from the signals by exploiting the ambient temperature; then, the estimation residuals are combined with the local temperature, sensor by sensor, to attenuate the influence of daily thermal cycles, also called micro-trends. Beyond the simple visual check of the time histories before and after the data cleaning procedure, the performance is evaluated according to two quantitative parameters computed over the whole period: the correlation coefficient between the temperature and the signals and the standard deviation of the latter, as a metric for the statistical variability. Furthermore, to highlight the relevance of the micro-trend, the mean values of the weekly computed standard deviation are calculated before and after the second step of the methodology, and next the seasonal effect removal.

Looking at the details of the algorithm, three main phases might be identified:

1. A K-means clusterisation (with K equal to two) is applied to identify the summer and winter months automatically, according to some features extracted from the signals, such as temperature ranges and temperature means.

2. A linear regression is carried out separately in the summer months and in the winter months. The regression takes as input the environmental temperature and it predicts the reading of every sensor. The residuals between the true measurements and the values estimated are computed.

3. By applying the cross-correlation between the residuals (computed at phase 2) and the local temperatures, the delay between the latter and the residual is estimated for every month and every sensor. The delay is then exploited to carry out a further regression. The new residuals, achieved by subtracting the residuals obtained at phase 2 and the values estimated by this new regression, are finally regarded as the measurements purged from the temperature effects.

RESULTS AND DISCUSSION

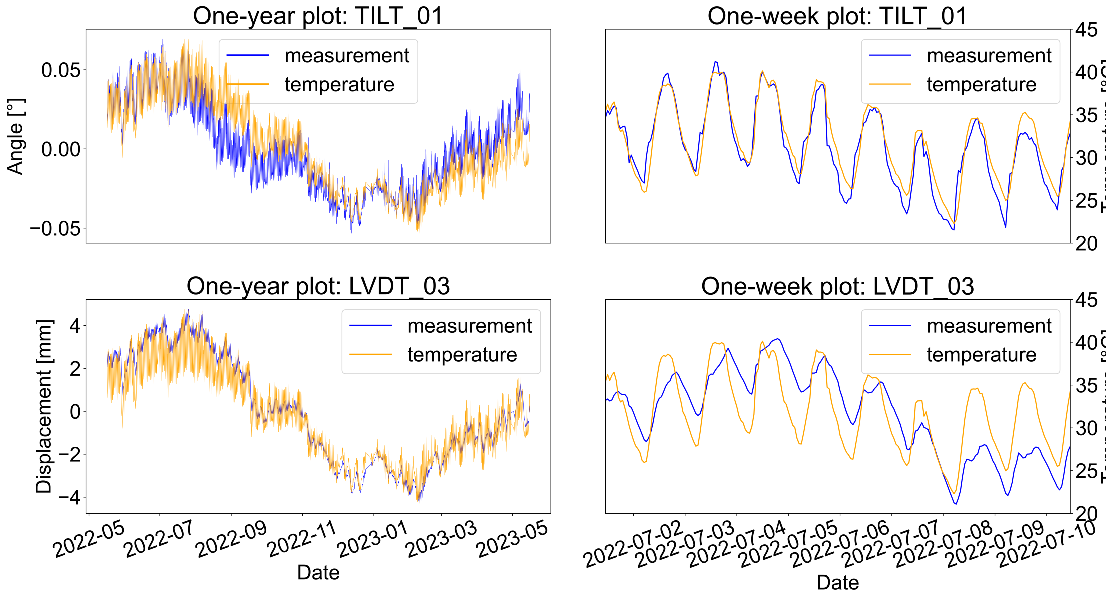

Figure 4. Visualization of the correlation between static measures and external temperature. On the left the yearly raw data of a tiltmeter (top) and an LVDT (bottom) compared to temperature to show the seasonality effect, also called macro-trend; on the right the same data, but zooming into a shorter window to highlight the daily temperature-induced oscillations, the so-called micro-trend.

This section presents the results of a temperature effect mitigation technique applied to static signals from two railway bridges. First, to highlight the influence of temperature on rotations and displacements, measurements from a tiltmeter and an LVDT are plotted with respect to the external temperature in one year (Figure 4). The plots evidence the twofold influence of temperature: the macro-trend is better visualized in the yearly span, while zooming into a shorter time window the micro-trend emerges. Beyond a graphical comparison, the two phenomena are numerically proved by the high correlation coefficients between temperature and measures, reported, for the two bridges, in Tables I and II. Such tables also provide the standard deviations of the signals, calculated considering two time windows, yearly and weekly, as a metric to evaluate their variability due to macro and micro-trend. This kind of table is used throughout this section to highlight the effect of the two steps of the methodology presented in this paper.

TABLE I. Parameters of interest to evaluate the methodology's performance. Correlation coefficient; yearly standard deviation; yearly average of the standard deviation computed weekly. Values referred to raw data from sensors installed on the CACP bridge.

Sensor	**corr**	$\mathbf{std_{year}}$	$\mathbf{std_{week}}$
TILT_01	0.899	0.027°	0.009°
TILT_02	0.951	0.018°	0.003°
LVDT_01	0.971	2.47 mm	0.23 mm
LVDT_02	0.964	2.62 mm	0.32 mm

TABLE II. Parameters of interest to evaluate the methodology's performance. Correlation coefficient; yearly standard deviation; yearly average of the standard deviation computed weekly. Values referred to raw data from sensors installed on the Warren truss bridge.

Sensor	**corr**	$\mathbf{std_{year}}$	$\mathbf{std_{week}}$
TILT_03	0.818	0.010°	0.005°
TILT_04	0.845	0.006°	0.003°
LVDT_03	0.972	2.46 mm	0.31 mm
LVDT_04	0.919	0.47 mm	0.10 mm

First, the initial part of the algorithm attenuates the seasonal effect on the measures by taking in input the external temperature. As shown in tables III and IV, the operation successfully removed the macro-trend, nullifying the correlation coefficients and decurting the yearly standard deviations. While such a result is consistent for all sensors, a different behavior arouse regarding the mean values of the weekly standard deviation, which diminished for tiltmeters but increased for LVDTs. To complete the signal processing, the residuals, calculated as a difference between the raw signals and their temperature-based estimation from the previous step, are processed to treat the micro-trend. Given the more local nature of the phenomenon, the temperature measured by each sensor is used as input to the model. The usual tables summarize the results of this last step (Tables III and IV). In this case, yearly values of standard deviation and correlation coefficient have not been much affected, as expected, but the situation on the weekly horizon has improved, with a reduction of the short-term variability for both sensors.

TABLE III. Parameters of interest to evaluate the methodology's performance after the two steps are applied. Correlation coefficient; yearly standard deviation after step 1; yearly standard deviation after step 2; yearly average of the standard deviation computed weekly after step 1; yearly average of the standard deviation computed weekly after step 2. Values referred to sensors installed on the CACP bridge.

Sensor	**corr**	$\mathbf{std^1_{year}}$	$\mathbf{std^1_{week}}$	$\mathbf{std^2_{year}}$	$\mathbf{std^2_{week}}$
TILT_01	0.006	0.011°	0.004°	0.004°	0.003°
TILT_02	-0.101	0.006°	0.004°	0.004°	0.003°
LVDT_01	-0.148	0.57 mm	0.43 mm	0.47 mm	0.39 mm
LVDT_02	-0.125	0.68 mm	0.51 mm	0.56 mm	0.47 mm

TABLE IV. Parameters of interest to evaluate the methodology's performance after the two steps are applied. Correlation coefficient; yearly standard deviation after step 1; yearly standard deviation after step 2; yearly average of the standard deviation computed weekly after step 1; yearly average of the standard deviation computed weekly after step 2. Values referred to sensors installed on the Warren truss bridge.

Sensor	**corr**	$\mathbf{std^1_{year}}$	$\mathbf{std^1_{week}}$	$\mathbf{std^2_{year}}$	$\mathbf{std^2_{week}}$
TILT_03	0.040	0.005°	0.002°	0.003°	0.002°
TILT_04	0.005	0.003°	0.001°	0.002°	0.001°
LVDT_03	-0.117	0.56 mm	0.41 mm	0.46 mm	0.38 mm
LVDT_04	-0.121	0.18 mm	0.11 mm	0.13 mm	0.10 mm

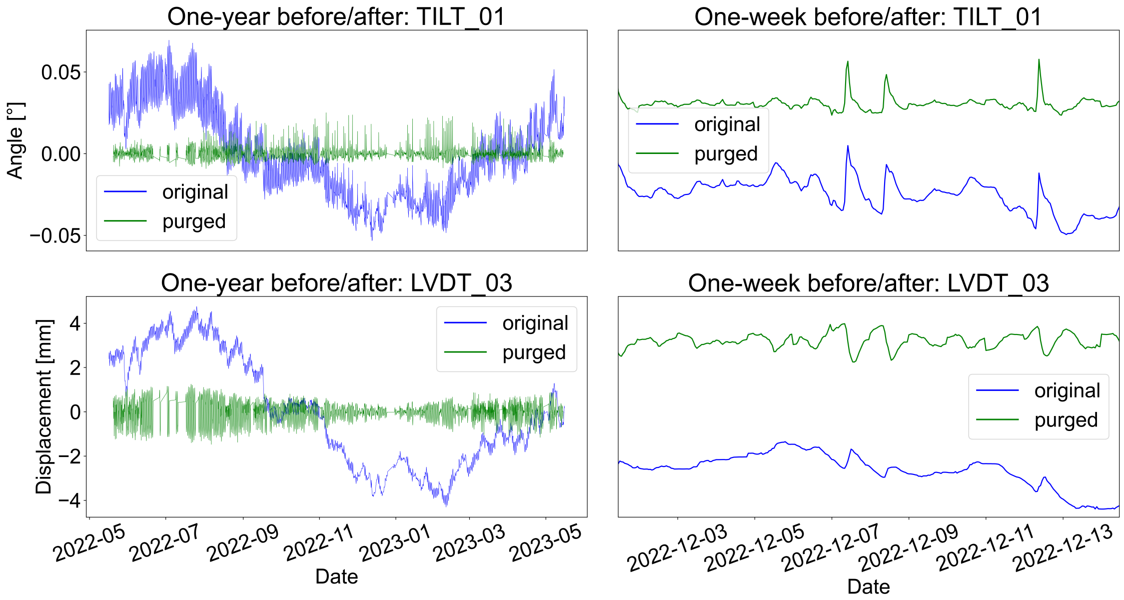

Figure 5. Visualization of the results of the methodology in terms of reduction of both seasonal and daily temperature effect. On the left a comparison between raw and clean data of a tiltmeter (top) and an LVDT; on the right the same data, but zooming into a shorter window to highlight the effect of the technique on the micro-trend.

For a more visual understanding of the results achieved by this methodology, a comparison between the raw signals and the purged ones is provided in Figure 5 by referring to the same tiltmeter and LVDT used in Figure 4.

CONCLUSIONS AND FURTHER DEVELOPMENTS

This paper presents a statistical learning algorithm aimed at removing the effect of temperature on static signals collected for a year by tiltmeters and LVDTs used for bridge structural health monitoring. Both the seasonal and daily temperature cycles have been considered, also referred to as macro-trend and micro-trend, respectively. The methodology has been tested on two railway bridges featuring different structural characteristics to assess its generality, and it proved to reduce the temperature dependence substantially and, in turn, the variability of the signals. Correlation coefficients and standard deviations have been exploited as metrics, and they were calculated on time windows of different lengths to investigate both the seasonal and daily cycles. The herein-proposed algorithm enables purging static signals from the temperature influence, reducing the non-structural contributions that might hide the effect of possible damage, especially in its early stage. Better performance was achieved on signals from tiltmeters, where both trends were reduced. Conversely, the seasonal trend was removed from LVDTs by the first step of the algorithms but amplifying the daily effect. Such a downside has been mitigated by the second step, which proved to be a valuable additional contribution even in the case of displacement measures. However, this difference between tiltmeters and LVDTs deserves further investigation, which constitutes the most natural next step for future methodology improvements.

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