Structural identification through continuous monitoring: data cleansing using temperature variations

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Abstract

The aim of structural performance monitoring is to infer the state of a structure from measurements and thereby support decisions related to structural management. Complex structures may be equipped with hundreds of sensors that measure quantities such as temperature, acceleration and strain. However, meaningful interpretation of data collected from continuous monitoring remains a challenge. MPCA (Moving principal component analysis) is a model-free data interpretation method which compares characteristics of a moving window of measurements against those derived from a reference period. This paper explores a data cleansing approach to improve the performance of MPCA. The approach uses a smoothing procedure or a low-pass filter (moving average) to exclude the effects of seasonal temperature variations. Consequently MPCA can use a smaller moving window and therefore detect anomalies more rapidly. Measurements from a numerical model and a prestressed beam are used to illustrate the approach. Results show that removal of seasonal temperature effects can improve the performance of MPCA. However, improvement may not be significant and there remains a trade off when choosing the window size. A small window increases the risk of false-positives while a large window increases the time to detect damage.

Keywords: Structural identification, data interpretation, thermal response, anomaly detection.

1 Introduction

Current sensor technology and data acquisition systems enable continuous monitoring of structural behavior. Complex structures may have many types of sensors to measure environmental parameters such as temperature, pressure, wind speed and response characteristics such as acceleration and strain. Quasi-static monitoring consists of continuously acquiring values of parameters related to environmental characteristics and system response to ambient excitation at a rate that does not necessarily capture the full dynamic response, thus producing time series of instrumentation data that are potentially informative. While this leads to massive amounts of data, measurement interpretation, which is the core task in structural identification, remains a challenge.

In structural performance monitoring, there are two main classes of data interpretation methods and they are distinguished by the use or absence of physics-based behaviour models. The two types of methods are complementary since they are most appropriate in different contexts. In the ASCE state-of-the-art report on structural identification of constructed systems (ASCE, 2009), a summary of the strengths and weaknesses of the two classes of methods is provided in a chapter on data interpretation.

Models can support decisions related to long-term structural management such as estimation of reserve capacity and repair. However, models are expensive to build and identifying a unique model is difficult due to uncertainties. Furthermore many model predictions might approximately match observations and due to compensating errors, the best matching model may not be the correct model (Smith and Saitta, 2008). Robert-Nicoud (2003) developed a system identification methodology that involves a strategy of generation and filtering of sets of candidate models. Also Robert-Nicoud et al. (2005) were the first to use multiple models explicitly for structural identification. Users input measurement data and specify sets of modelling assumptions related to the structure. The model selection process (Raphael and Smith, 2003) identifies a set of candidate models whose predictions best match the measurements.

The majority of model-based methods developed for structural identification involve vibration-based monitoring (Doebling et al., 1998). Ambient vibration–based modal analysis has been used to observe changes in modal parameters (Brownjohn, 2009). This area has received much attention in the last decade (Fritzen and Kraemer, 2009, Magalhães et al., 2009, Reynders and De Roeck, 2009, Shoukry et al., 2009, Yang et al., 2009, Yin et al., 2009). Only a few researchers (Caddemi and Morassi, 2007, Matta et al., 2008, Sanayei and Saletnik, 1996, Shenton and Hu, 2006) have focused on evaluating static response. This is paradoxical since the static case has less theoretical complexity when compared with modal and transient dynamic evaluations and it is also valuable as input into dynamic studies (Hjelmstad and Shin, 1997).

Model-free data interpretation methods are better-suited for analyzing measurements from continuous monitoring of structures since they are generally statistical and do not require knowledge of the structural behaviour. Omenzetter et al. (2004) used discrete wavelet transform to detect sudden changes in strain histories. Omenzetter and Brownjohn (2006) proposed an autoregressive integrated moving average (ARIMA) model to detect damage from measurement histories. Lanata and Grosso (2006) suggested proper orthogonal decomposition for damage detection and localization. However, these methods are often not applicable in practice since datasets have outliers and are often incomplete due to missing measurements.

Posenato et al. (2008, 2010) showed that moving principal components analysis (MPCA) is the most appropriate for continuous monitoring of civil engineering structures. MPCA was combined with pre-processing methods to clean datasets. MPCA has many advantages over principal component analysis (PCA) for continuous monitoring. For example it calculates process parameters more rapidly since the computation time for each step is constant being a function only of the window size. Detection of new events is more accurate and faster than PCA since old measurements do not buffer results.

Posenato's approach relies on the structural response to temperature variations to detect anomalies. Temperature is an important factor influencing the performance and serviceability of bridges. For example, Brownjohn et al (2009) studied the thermal effects on performance on Tamar Bridge and showed that thermal effects dominate the measured bridge behaviour. Catbas et al. (2008) observed that the peak-to-peak strain differential due to temperature over a one-year period is more than ten times higher than the strain due to observed maximum daily traffic. A key parameter in MPCA is the dimension of the moving window. As the method relied on the patterns due to seasonal temperature variations, a minimum window size of two years was recommended. Moreover, a window size of two years implies that a long reference period of two years is required for training purposes. Environmental aspects also found to have a significant effect on the quality of results.

This paper introduces a data cleansing method to remove the seasonal temperature variations in the datasets and thereby reduce the time to detect anomalies using MPCA. Although influence of temperature variation on structural behaviour has been acknowledged by many researchers in this field, few have accounted for this variation in their methods for structural performance evaluation. Two case studies are used to illustrate the approach.

2 Moving average filtering

The moving average filter is used to remove seasonal temperature variations from the measurement series. This is the most common filter in signal processing, mainly because it is the easiest filter to understand and use (Smith, 1997).

The moving average filter used in this study is a center moving average with flat weighting (Smith 1997). It smoothes data by replacing each data point with the average of the neighboring data points defined within the span. This process is equivalent to lowpass filtering with the response of the smoothing given by the difference equation:

$$y_s(i) = \frac{1}{2N+1}(y(i+N) + y(i+(N-1)) + ... + y(i-N)) \tag{1}$$

where $y_s(i)$ is the smoothed value for the ith data point, N is the number of neighboring data points on either side of $y_s(i)$, and $2N+1$ is the span.

3 Moving principal component analysis (MPCA)

MPCA is used to analyze datasets obtained after filtering measurement histories using a moving average filter. MPCA was first proposed for the interpretation of measurements from continuous monitoring by Posenato et al. (2008) . MPCA essentially applies principal component analysis (PCA) (Hubert and Verboven, 2003) to a sliding window of measurements instead of the whole dataset.

MPCA consists of the following steps when applied to measurement histories from N_s number of sensors.

1. Construct a matrix U that contains the history of all the measured parameters as shown in Equation 1.

$$U(t) = \begin{bmatrix} u_1(t_1) & u_2(t_1) & \dots & u_{N_s}(t_1) \\ u_1(t_2) & u_2(t_2) & \dots & u_{N_s}(t_2) \\ \dots & \dots & \dots & \dots \\ u_1(t_{N_w}) & u_2(t_{N_w}) & \dots & u_{N_s}(t_{N_w}) \\ \dots & \dots & \dots & \dots \\ u_1(t_N) & u_2(t_N) & \dots & u_{N_s}(t_N) \end{bmatrix} \tag{1}$$

   N represents the total number of observations during the monitoring period.

2. Iteratively extract datasets corresponding to a sliding window of size N_w (see Equation 2)

$$W(j) = \begin{bmatrix} w_1(t_j) & w_2(t_j) & \dots & w_{N_s}(t_j) \\ w_1(t_j) & w_2(t_j) & \dots & w_{N_s}(t_j) \\ \dots & \dots & \dots & \dots \\ w_1(t_{j+N_w}) & w_2(t_{j+N_w}) & \dots & w_{N_s}(t_{j+N_w}) \end{bmatrix} \tag{2}$$

3. For each of window measurements, evaluate the principal components using PCA.

The principal components are the eigenvectors of the covariance matrix of measurements W. The eigenvectors corresponding to the largest eigenvalues represent the most persistent time functions

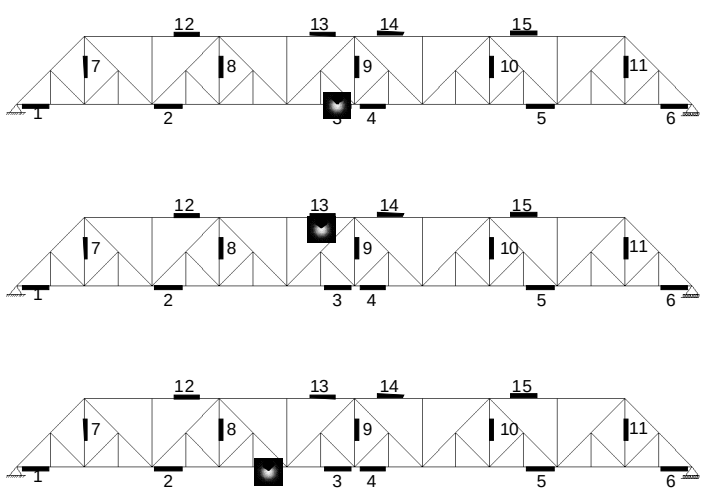
with the greatest variance. When damage occurs, mean values and components of the covariance matrix change and as consequence, so do values of eigenvalues and eigenvectors.

A key issue is selecting the dimension of the window (N_w). If the process is stationary it is necessary to select a value N_w that is sufficiently large so that it is not influenced by measurement noise. If the time series has a periodic behaviour (for example, due to temperature cycles) the choice of the window size should be a multiple of the period. This choice ensures that mean values are stationary over time and that eigenvalues of the covariance matrix do not have periodic behavior.

4 Case studies

4.1 Truss model

A numerical model of a truss bridge inspired from the railway bridge in Zangenberg, Germany is used. Only one truss is modelled in this study. Figure 1 shows the truss model and the virtual sensor placement. The numbers represent sensor numbers and the dots mark the location where damage is introduced. Traffic load is simulated by introducing a vertical load of random value (0-19 tons) at each node in the bottom chord. Damage is modelled as stiffness reduction in chosen element for each scenario. For this case study, 3 different damage scenarios are introduced. In the first damage scenario, damage is introduced at the mid span in the bottom chord right at the place where sensor 3 is placed. In the second scenario, damage is introduced at mid span top chord at the same element where sensor 13 is placed. As for the third scenario, damage is introduced in an element between sensors 2 and 3. This scenario is meant to check the availability of MPCA to detect damage when damage occurs not directly on the place where sensor is placed. Figure 2 shows the time history of strain measurements from sensor 13 for the second scenario. Damage is introduced at day 760 which is not recognizable from the plot due to temperature variations.



Scenario 1 : Damage at bottom chord midspan (stiffness reduction of 10 %)

Scenario 2 : Damage at top chord midspan (stiffness reduction of 10 %)

Scenario 3 : Damage at bottom chord (stiffness reduction of 20 %)

Figure 1 Damage scenarios (bars and dots represent location of sensors and introduced damage respectively)

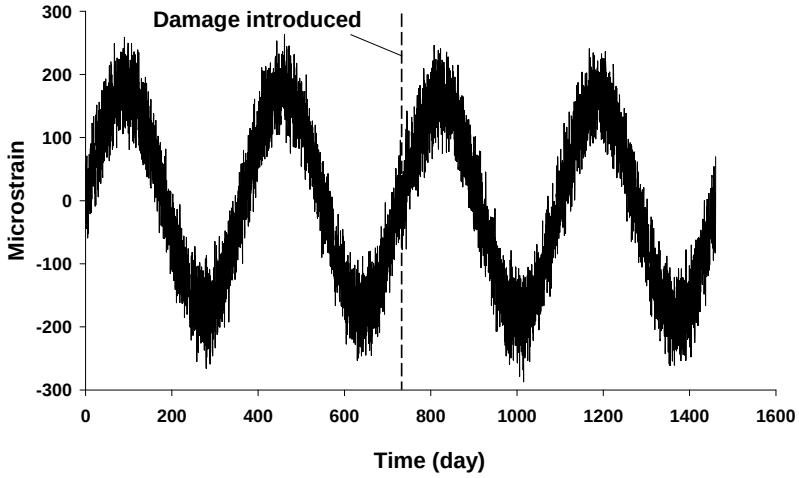


Figure 2 Strain time history of sensor 13 in scenario 2

MPCA is applied for anomaly detection. As the time series is periodic due to seasonal temperature variations, a window size of three years (two years for seasonal temperature variations and one year for noise) is required (Posenato et al. 2006) when temperature effects are not removed. Therefore, MPCA may require a period of three years to detect an anomaly. By removing temperature effects from measurement data, the window size can be reduced.

Figures 3 - 5 show the results from MPCA. The time delay in detecting damage when having and removing temperature effects for all damage scenarios is shown. A ±3-sigma confidence interval calculated from eigenvector variations in the reference period is used to create thresholds. When the eigenvectors take values outside the threshold, an anomaly is assumed to be detected.

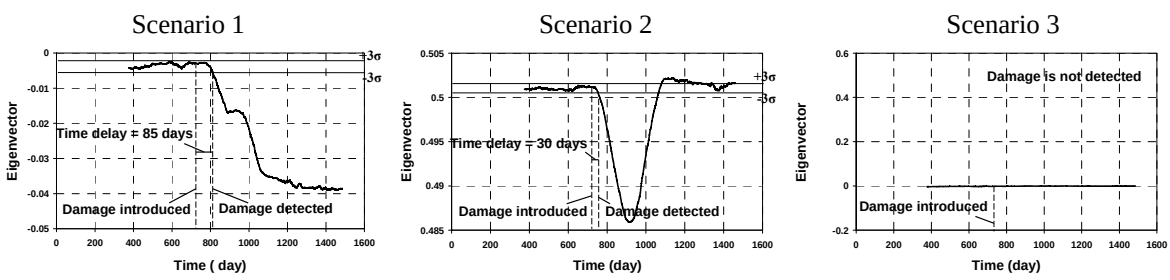


Figure 3 MPCA results (measurements with temperature effects)

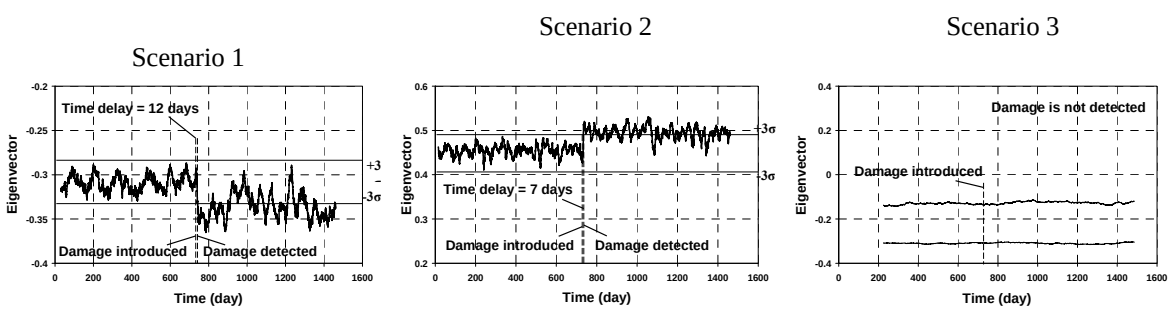


Figure 4 MPCA results (without temperature effects. No temperature loading is applied to structure)

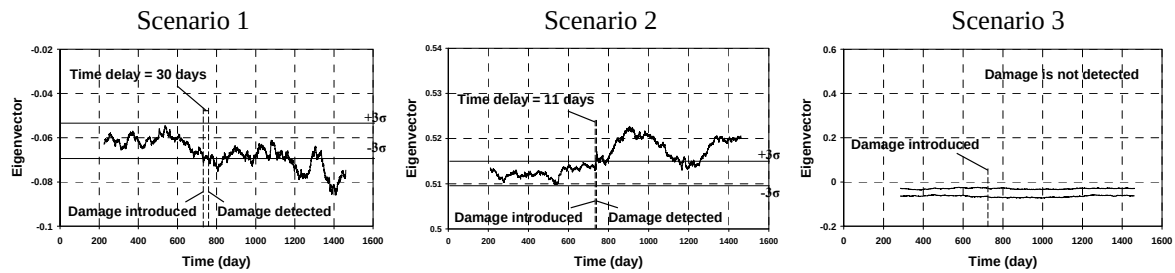


Figure 5 MPCA results (temperature effects removed using moving average filter)

Without removing seasonal temperature effects, MPCA was able to detect damage in scenarios one and two with a time delay (figure 3). Scenario 3 was not detected. After removal of temperature effects, MPCA is able to detect anomalies faster using a smaller window. When there is no temperature load applied to the structure, time delays appear to be shorter (figure 4). This shows that MPCA performs better without temperature effects.. When using moving average (figure 5), temperature effects are not fully removed and as a result the eigenvector variation is not stable thereby making detection less reliable. Figure 6 shows a plot of the detection time delay with different window sizes. After the removal of temperature effects, smaller window sizes generally enable faster anomaly detection. However, the trend is not monotonic. The results show that the approach while being able to detect damage faster for scenarios one and two, still fails to detect damage in scenario 3.

Larger window sizes give smaller variations or more stability in calculated eigenvector histories which makes the changes more visible. The drawback is that time delay in detecting an anomaly also increases with the length of the moving window. On the other hand, smaller window sizes, while decreasing the time delay in anomaly detection, lead to larger variations in the eigenvector histories and thereby make it harder to detect changes.

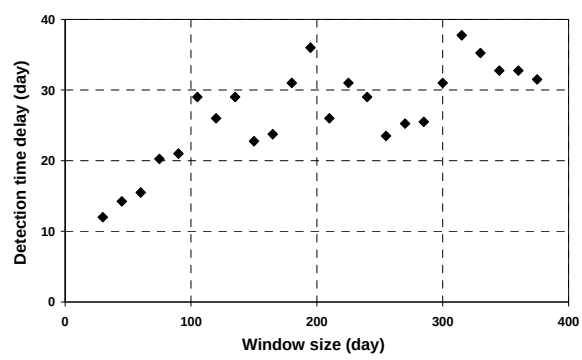


Figure 6 Detection time delay for different moving window sizes (scenario 1, sensor 3)

4.2 Prestressed beam

This experimental test was performed at the University of Genoa with cooperation from SMARTEC. It is a post-tensioned concrete beam of 8 m in length with a rectangular cross section (0.25 m large and 0.40 m height). The beam is located outside in the open air and left exposed to the external environment. The beam is instrumented with eight optic deformation sensors (SOFO sensors) and four thermocouples on the upper and lower beam surfaces (Figure 7). Measurements are taken four times per hour and damage is introduced in stages in the mid-span of the beam. Table 1 shows the dates of the events. Figure 8 shows the deformation and temperature time histories obtained during the monitoring period.

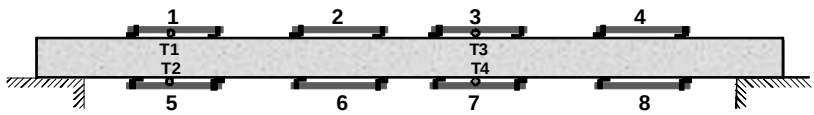


Figure 7 Sensors in the prestressed beam test (1-8 deformation sensors, T1-T4 Thermocouples)

Table 1 List of events introduced to the prestressed beam

#	Date	Event
0	14.04.2008	Installation of the monitoring system
1	08.05.2008	Extra dead load
2	18.06.2008	1st artificial damage (1 cm cut)
3	23.06.2008	2nd artificial damage (2 cm cut)
4	09.07.2008	3rd artificial damage (cut of half of the first rebar)
5	16.07.2008	4th artificial damage (cut of the first rebar)
6	22.08.2008	Storm

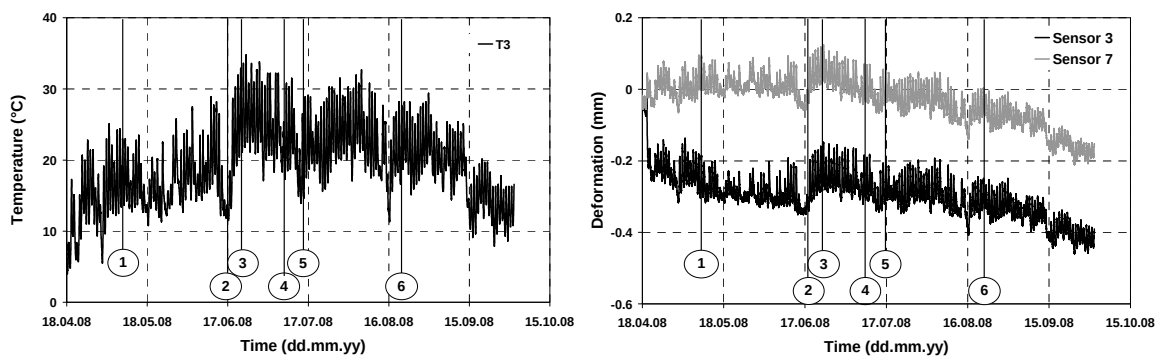


Figure 8 Temperature and deformation time measurement time history

Seasonal temperature variations are first filtered out as follows. Moving average filter is used to extract the seasonal temperature variation. The temperature changes produced by the seasonal variation are multiplied by the coefficient of thermal expansion to approximate the seasonal deformation variations. Seasonal temperature effects are consequently removed by subtracting the predicted temperature response from the original deformation measurements.

MPCA is used for data interpretation. Figure 9 shows eigenvectors extracted from the covariance matrix of the measurements from the eight SOFO sensors before and after temperature effects removal. Before removal of temperature effects, eigenvector history is very unstable, hence events are not detected. Seasonal temperature variations in measurements are then removed using the moving average filter. There are two jumps or changes observed from both analyses in the eigenvector history which correspond to events 2 and 4. However there are no significant changes corresponding to events 3 and 5. The reason is that the time interval between damage events is shorter than the window size. MPCA is unable to detect the damage if the time from the previous detected anomaly is shorter than the window size. Another reason for not detecting events is insufficient reference period. The period between the installation and the introduced events is only 2 months. This reference period is not long enough to cover all the variations due effects other than damage. Such short reference periods decrease the reliability of the algorithm to detect anomalies.

With temperature variation

Without temperature variation

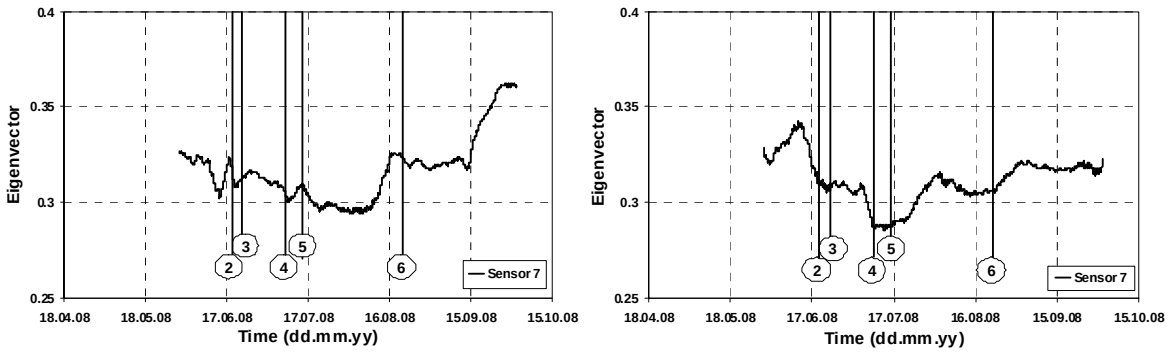


Figure 9 MPCA results before and after temperature effects removal

5 Conclusions

The paper presents an approach for removing temperature effects from measurements and investigates the effects of the removal on the performance of MPCA in detecting anomalies for structural identification. The conclusions from this study are as follows.

- MPCA performs better after cleansing the data of seasonal temperature effects. However, the method is still unable to detect damage at locations further away from sensors.
- Stability of eigenvectors within the reference period is required for the MPCA to detect anomalies. Therefore a sufficiently large reference period is recommended to cover all variations of eigenvectors that are not related to damage.
- MPCA requires a time interval between two consecutive damage events that is more than the length of the moving window. Such an interval is essential to allow MPCA to adapt to the new state of the structure after a damage event.
- Results from the case studies show that the removal of temperature effects from measurement data may improve the performance of MPCA.

The criteria for anomaly detection are based on thresholds that are evaluated as ±3 times the standard deviation of the values for the eigenvector in the reference period. Future work will investigate methods to estimate a threshold value which incorporates uncertainties in the data cleansing step and stability of eigenvectors.

Acknowledgements

This work was funded in part by Swiss Commission for Technology and Innovation under Contract number CTI-8613-1. Authors would also like to thank Daniele Posenato, Francesca Lanata and the University of Genoa for the measurements on the prestressed beams. Daniele Inaudi, Andrea Del Grosso and Smartec SA are also thanked for their contributions.

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