Damage Detection on the NPL Footbridge Under Changing Environmental Conditions

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ABSTRACT

Over the years 2009 to 2011, a full-scale footbridge was the subject of a comprehensive monitoring campaign at the UK's National Physical Laboratory. The footbridge was densely instrumented with a variety of different sensors covering diverse modalities. The bridge was monitored in its normal undamaged condition over an extensive period covering a wide range of seasonal variations in its environment. At times in the monitoring campaign systematic damage was introduced. For structural health monitoring of the bridge an unsupervised learning approach, or novelty detection, is desirable, where one assumes that only measurements of the normal condition are available to define a baseline. The standard issue then arises of projecting out the environmental variations from feature data so that alarms are not raised as a result of benign changes. In the current paper, the means of removing the environmental effects is via the use of the cointegration algorithm, which has recently been adapted for this purpose from the discipline of econometrics. Damage detection results are presented based on the use of Statistical Process Control (SPC) algorithms. The results are shown to be consistent with the history of the bridge throughout the experimental campaign.

INTRODUCTION

The footbridge which is the basis of the current paper has been at the centre of a comprehensive Structural Health Monitoring (SHM) exercise at the National Physical Laboratories (NPL) since the year 2008. The footbridge was actually in use at the NPL site for over 40 years; when site development required its relocation, it was adopted as a test structure.

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The bridge was densely instrumented with sensors covering a multitude of different physical quantities which were thought to show promise as features for damage detection. Only the tilt sensors installed on the bridge will be considered in this study; for a detailed description of the other sensors and more comprehensive background on the bridge, the reader may consult [1]. One aspect of the monitoring campaign which became apparent at an early stage was that, because the bridge is outdoors like most civil engineering structures, the sensor readings were subject to, and in many cases dominated, by environmental variations [2]. It is well known by now that one of the main issues in SHM is the fact that changes in measured quantities from a structure due to environmental and operational variations may be much larger than changes due to damage [3]. This problem is most severe if one adopts a *novelty detection* approach to SHM. In such an approach, only data from the normal condition of the structure is used to build a statistical model; if subsequent data deviate from this model, one infers damage. The problem with this approach when environmental and operational variations are present is evident; if a new environmental or operation condition occurs, the method will signal change and a false positive indication of damage will occur. There are a number of proposed solutions to this problem as discussed in [3]; perhaps the most elegant of these involve projecting out the influence of the environmental or operational parameters. A recent addition to these projection methods is based on cointegration [4], a technique adapted from the econometrics literature, and it is this approach will be adopted here for the analysis of the footbridge data. Having removed the effect of environmental and operational variations, one is still left with a choice of which novelty detection procedure to employ and a simple Statistical Process Control (SPC) approach is adopted here.

Subsequent sections of the paper will cover a description of the NPL footbridge together with aspects of the monitoring campaign and data selected for analysis, a brief summary of the cointegration method and a summary of the results of a damage detection analysis for the data.

THE NPL FOOTBRIDGE

The footbridge is a substantial concrete structure, weighing 15 tonnes and 20m long by 5 m high. As discussed earlier, at the start of the monitoring campaign in 2008 the bridge was instrumented with a large number of sensors with different modalities. The sensors of interest for this study are a set of tilt sensors. The tilt sensors measure the local slope of the structure and are therefore sensitive to any distortion of the bridge geometry that might result from damage. The tilt sensors used were Electrolevel Beam Tilt Sensors and were provided and installed by Soil Instruments (now ITMSOIL) [1]. Figure 1 shows a schematic of the bridge showing the location of the eight tilt sensors. A number of thermometers were also installed and in general these would be important in quantifying the degree of environmental change experienced across the structure; however, the readings will not be used in the analysis here as the cointegration method is able to remove environmental and operational variations without measurements of the associated variables or parameters. Figure 1 also indicates the point of application of the load induced during testing.

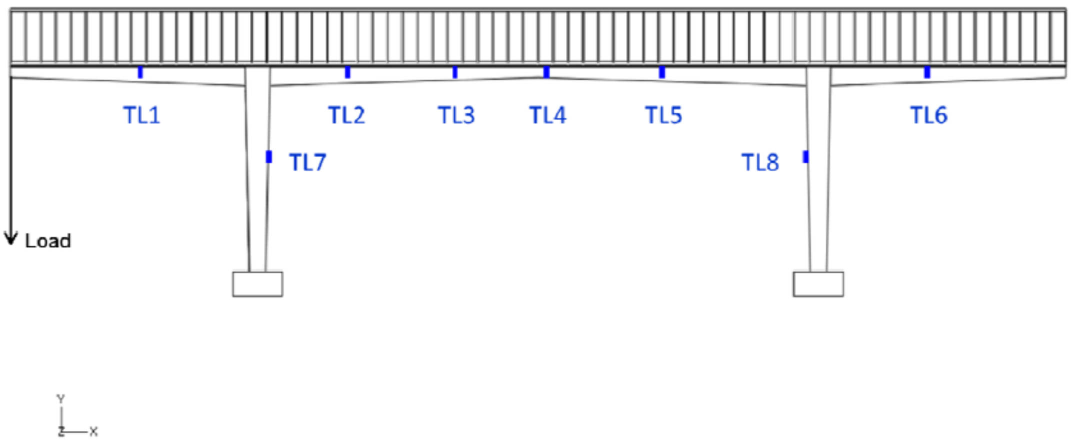

Figure 1. Schematic of the footbridge showing the location of the tilt (TL) sensors.

After its relocation and reassignment as a test structure the bridge was subjected to a detailed structural survey which concluded that it was in good structural condition. No cracking was observed in the surface or soffit of the deck although some damage was inferred in the columns as a result of observed distortion.

The first major test programme on the bridge was conducted in the spring and summer of 2009. Over a period of six months the bridge was subjected to a series of static short-term and sustained loading tests. The objectives of the tests were: to induce displacements in the structure at the upper bounds of the serviceability limits; to induce sufficient tensile strains to cause concrete cracking; to simulate reinforcement corrosion; to attempt to assess structural performance using data from the sensor networks. Loading was imposed using water tanks suspended at the point indicated on Figure 1 with an arrow at the end of a cantilever portion of the deck; maximum loads of 22kN were achieved. Subsequent inspection showed that the concrete had indeed cracked with the main area of damage in the left hand column in Figure 1 above the tilt sensor TL7. Data from this first phase of testing were analysed and it proved possible to infer a change in structural condition between the pre-test and post-test regimes [2].

The data considered here are from the tilt sensors and cover the period from February 2009 to September 2011. In order to use cointegration to remove the effects of environmental variations – temperature variation appeared to dominate in this case [2] - it is sensible (although not always necessary) to capture all possible variations in a *training data* set. For the current problem, this meant that a year's data were used to establish a baseline condition including all possible environmental variations. The training data selected here were taken from the period February 2009 to February 2010; this meant that the structure experienced damage during the period covered by the training set. This is not a problem from the point of novelty detection; the analysis begins with a baseline including some damage rather than one for an undamaged structure and the question is then if the algorithm can detect further deterioration. In the programme of tests following February 2010, there were four events which may well have caused further deterioration:

- From 30th June 2010 to 2nd July of 2010 further static tests were carried out involving loading and unloading the structure using the water tanks.

- On the 18th October 2010, deliberate damage was introduced in the form of a cut to a rebar.
- On the 28th April 2011, a further cut was made and a portion of damaged concrete was removed on the 6th May 2011.
- On the 27th June 2011, a further cut was made.

Over the period, a number of other events occurred including some less significant static tests; some attempts at repair were also carried out.

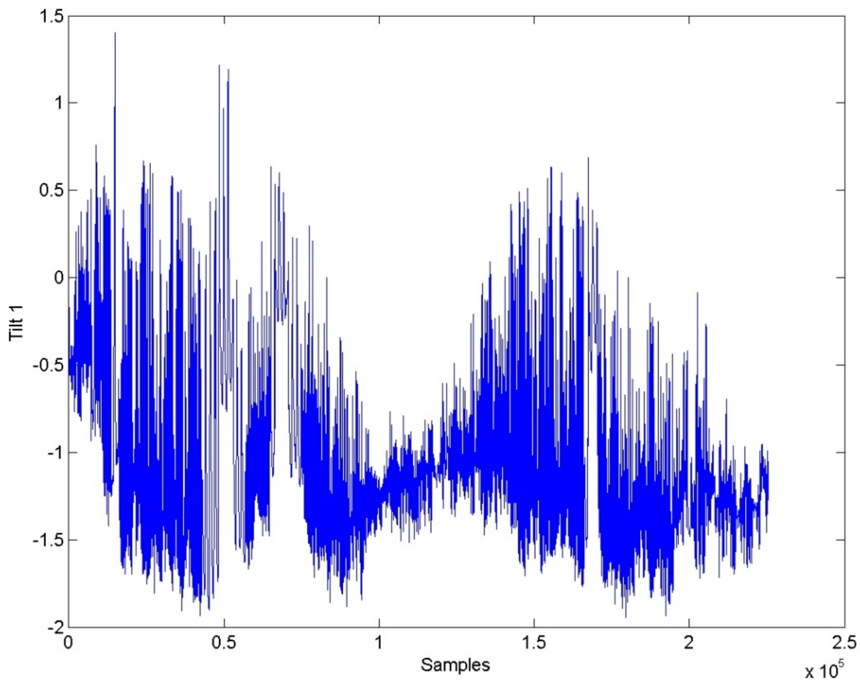

Figure 2. Tilt Sensor 1 readings covering a period of almost two years.

Figure 2 shows the readings from Tilt Sensor 1 over the period February 2009 to January 2011. The very clear nonstationarity in the signal is largely the result of temperature variations [2]; globally the seasonal variation is evident; at a local scale daily variations are also obvious. It is clear that detection of damage against such a background of environmental variations is a challenging problem. In the current paper the problem is addressed by using the cointegration method to create a univariate 'residual' signal that is purged of environmental variations which can then be used for damage detection. The basis of the method is that multiple tilt sensors will yield signals which share the temperature trends; a linear combination of the signals can then be formed to cancel the trends. The cointegration method will be briefly outlined in the next section.

THE BASICS OF COINTEGRATION

The theory is based on the premise that an *n*-dimensional vector of time series $\{y_i\}, (i = 1, \ldots, T)$, has been measured and that the appropriate model for the system is a Vector-AutoRegressive (VAR) process of the form,

$$\{y_i\} = \sum_{j=1}^{p} [A_j]\{y_{i-j}\} + \{D(t)\} + \{\varepsilon_i\} \tag{1}$$

where p is the AR order of the process, the $[A_j]$ are coefficient matrices, $\{D(t)\}$ is a (possible) vector of deterministic trends and $\{\varepsilon_i\}$ is a vector of stationary white noise sequences. In general, the series $\{y_i\}$ may be nonstationary; the idea of cointegration is that, under certain conditions, there may exist a stationary time series $z_i = \{\beta\}^T\{y_i\}$ formed from a linear combination of the original series. If a suitable $\{\beta\}$ exists, it is referred to as a *cointegrating vector*. It is clear that, for a cointegrating vector to exist, the original set of time series must share *common trends* in order that linear combination can remove them. In the context of SHM one can see that the existence of a single variable driving the environmental variations in a structure, like temperature, would lead to common trends in any multivariate response series measured from the structure. This means that cointegration can potentially be used to project out environmental variations from features extracted for diagnostic purposes. The issue of importance here is, if a series is nonstationary, *how nonstationary is it*? A technical definition is of use here: if a nonstationary process variable y becomes stationary after differencing d times, it is said to be integrated of order d, denoted as $z \sim I(d)$. Clearly $z \sim I(0)$ indicates that the sequence is stationary. A variable set $\{z\} = (z_1, \dots, z_n)^T$ (the sampling index is suppressed) is said to be cointegrated of order (d, b) if and only if [5];

1. All components of $\{z\}$ are integrated of the same order d.
2. There exists a vector $\{\beta\}$ such that $\xi = \{\beta\}^T\{z\} \sim I(d-b)$.
3. The components of $\{z\}$ are *cointegrated variables* and $\{\beta\}$ is a *cointegrating vector* if and only if $b = d$.

Condition 2 says that the order of integration is reduced by b on forming the linear combination. Condition 3 states that ξ is *stationary* if an appropriate cointegrating vector can be found. In fact, in many cases, multiple cointegrating vectors can be found.

The situation considered here will be the one where the response series $\{y_i\}$ is assumed to be $I(1)$, in which case, the difference series $\{z_i\} = \{y_i\} - \{y_{i-1}\}$ will be $I(0)$ (i.e. stationary). In terms of the difference series, a little manipulation of equation (1) leads to the form,

$$\{z_i\} = [\Pi]\{y_{i-1}\} + \sum_{j=1}^{p-1} [B_j]\{z_{i-j}\} + \{D(t)\} + \{\varepsilon_i\} \tag{2}$$

which is called a Vector Error-Correction Model (VECM). It is shown in [6] or [7] that (roughly) a sufficient condition for a cointegrating vector to exist is that $[\Pi]$ should be rank-deficient. Suppose that the $n \times n$ matrix $[\Pi]$ has rank $n-r$, then a basic theorem of linear algebra asserts that it will admit a decomposition $[\Pi]=[\alpha][\beta]^T$ where $[\alpha]$ and $[\beta]$ are both $n \times r$. It transpires that the columns of $[\beta]$ are (up to a linear transformation) the desired cointegrating vectors. In principle then, construction of the cointegrating vectors looks fairly straightforward; one fits a VAR model to the vector time series of interest and converts to the corresponding VECM. Once the matrix $[\Pi]$ is found, its decomposition leads directly to $[\beta]$. Unfortunately, things are not quite so straightforward; because $[\Pi]$ is rank-deficient, standard least-squares regression procedures cannot be applied to the parameter estimation problem. A more complex *reduced-rank regression* approach is required; this can be summarised in terms of the *Johansen procedure* ([8] p.165); a detailed discussion of this procedure is not possible in the limited space available here; suffice it to say that a principled approach is available whereby candidate cointegrating vectors can be computed. It is this approach which is adopted here.

ANALYSIS AND RESULTS

The basic data for analysis here were readings from eight tilt sensors taken from February 2009 to September 2011. The samples were largely taken at 5 minute intervals over that period; however, sampling was irregular and sometimes readings were taken at 1 minute intervals and occasionally hourly. The first task in the signal processing was to produce regularly sampled data. This task was fairly straightforward as all data were time-stamped. The time-stamps were therefore used to select samples taken on the hour. Once this was accomplished, the data covering the period February 2009 to February 2010 were selected to form the training set for cointegration as this period covered an entire year of temperature variation. The Johansen procedure was applied to the eight tilt signals in the training set to form a cointegrated residual. The most stationary residual was chosen for subsequent damage detection.

Damage detection was carried out here using an X-bar chart, a basic technique from Statistical Process Control (SPC) [9]. SPC allows one to detect anomalies in time series using techniques at a varying level of sophistication. The most basic control chart is the *X-chart*; the underlying principle is that, if the signal of interest is regarded as a Gaussian noise sequence, one can set alarm levels or *control limits* at 3 standard deviations above and below the signal mean for the training set data. Deviations of that order would only normally occur 0.3% of the time as a result of statistical fluctuations so substantial crossing of the alarm limits would infer that something has changed since training and in an SHM context this would infer damage as long as environmental and operational variables have been properly accounted for. The *X-bar chart* is a little more sophisticated in that the time series variable monitored is an average of the original signal over a sequence of short non-overlapping time windows referred to as groups. The X-bar chart has the advantages of suppressing noise by the averaging process and of making the summed variable more Gaussian (by the central limit theorem) and thus validating the choice of alarm limits in terms of standard deviations.

For the X- bar chart used here, a group length of 24 was used for the cointegrated residual essentially giving daily samples. The resulting chart is shown in Figure 3. The alarm limits are shown in the figure as horizontal dashed lines. The extent of the chart covers the whole data set from February 2009 to September 2011. The region between the beginning of the chart and the first (black) vertical line encompasses the training data. One can see that the cointegration procedure has rendered the residual at least stationary in the mean, some residual nonstationarity in variance remains. The second vertical line (blue) in Figure 3 corresponds to June 30th 2010 when the major static test occurred; after the training period but before the blue line the residual remains stationary and there are few alarms; after June 30th 2010 there is a clear and sustained departure above the upper alarm limit.

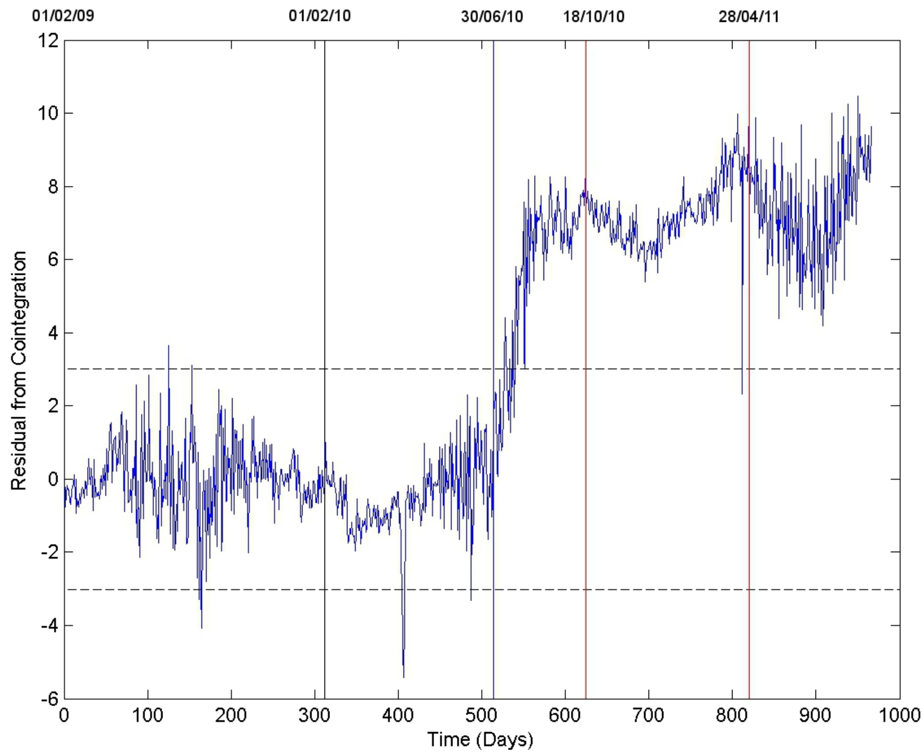

Figure 3. X-bar chart for residual after cointegration of tilt signals.

It was observed that when damage occurred after the March 24th 2009 load tests, the cracking was observed weeks after loading and continued steadily [1]. The results in Figure 3 are consistent with a similar gradual development of damage. The third and fourth vertical lines (red) in Figure 3 correspond to the deliberate damage introduced in October 2010 and April 2011. In order to detect any changes unambiguously, one would have to retrain here with data in the baseline condition resulting from the June/July 2010 load tests; however this is not carried out here as one would not necessarily have enough data to encompass an appropriate range of temperature variations. One observes though, that after the X-bar chart variable stabilises following the June/July 2010 tests, there are distinct dips at the red lines when damage was deliberately introduced. Although it may seem that that the residual is recovering following these events, it is more likely that the variation is due to the fact that, in the new states, the residual is no longer purged of the environmental variations. In fact, one should not properly refer to the residual as ‘cointegrated’ once the condition of the structure has changed from that when the training data were acquired.

CONCLUSIONS

Long conclusions are neither warranted nor needed here. In the context of this case study, the combination of cointegration and SPC appears to have detected possible damaging events against a background of significant environmental variation. This is consistent with the performance of cointegration in other studies where environmental and operational variations have proved problematic. One should be aware that the results presented here cannot be considered completely conclusive as the structure is complicated and damage of varying levels was already present in the structure when training data were selected. What is certain though is that the features of interest in the SPC chart certainly correspond to events in the life of the structure that are likely to have induced changes. Furthermore, no significant deviations occur in the chart at points that cannot be associated with events likely to cause damage. The results are not completely conclusive because it is not possible to eliminate, on the information given, the possibility that other factors may have caused deviations in the residual. For example, a plausible reason for an alarm is that one of the tilt sensors was disturbed during the testing; however, a close examination of the tilt sensors shows that readings are continuous across the test period.

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