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On switching response surface models, with applications to the structural health monitoring of bridges

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ABSTRACT

Structural Health Monitoring (SHM) is the engineering discipline of diagnosing damage and estimating safe remaining life for structures and systems. Often, SHM is accomplished by detecting changes in measured quantities from the structure of interest; if there are no competing explanations for the changes, one infers that they are the result of damage. If the structure of interest is subject to changes in its environmental or operational conditions, one must understand the effects of these changes in order that one does not falsely claim that damage has occurred when changes in measured quantities are observed. This problem – the problem of *confounding influences* – is particularly pressing for civil infrastructure where the given structure is usually openly exposed to the weather and may be subject to strongly varying operational conditions. One approach to understanding confounding influences is to construct a data-based *response surface model* that can represent measurement variations as a function of environmental and operational variables. The models can then be used to remove environmental and operational variations so that change detection algorithms signal the occurrence of damage alone. The current paper is concerned with such response surface models in the case of SHM of bridges. In particular, classes of response surface models that can *switch* discontinuously between regimes are discussed.

Recently, it has been shown that Gaussian Process (GP) models are an effective means of developing response surface or *surrogate* models. However, the GP approach runs into difficulties if changes in the latent variables cause the structure of interest to abruptly switch between regimes. A good example here, which is well known in the SHM literature, is given by the Z24 Bridge in Switzerland which completely changed its dynamical behaviour when it cooled below zero degrees Celsius as the asphalt of the deck stiffened. The solution proposed here is to adopt the recently-proposed Treed Gaussian Process (TGP) model as an alternative. The approach is illustrated here on the Z24 bridge and also on data from the Tamar Bridge in the UK which shows marked switching behaviour in certain of its dynamical characteristics when its ambient wind conditions change. It is shown that treed GPs provide an effective approach to response surface modelling and that in the Tamar case, a linear model is in fact sufficient to solve the problem.

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1. Introduction

In very brief terms, Structural Health Monitoring (SHM) is the engineering discipline concerned with inferring the state of health of a structure or system from measurements obtained from sensors permanently installed on the structure or within the system [1]. It is possible to exploit a very diverse range of sensor technologies in the implementation of an SHM system, but one of the more common choices is to monitor dynamical response using accelerometers. This choice leads to vibration-based SHM, and this is the main choice considered in this paper.

It is critical to note that an SHM system is much more than a sensor network. It is almost always the case that the information about the health of the structure is well hidden in the raw time series data acquired by sensing. This issue arises because small incipient damage will not usually cause a major departure from the dynamical behaviour of the healthy structure. Because of this fact, the vital ingredient in any SHM system is an inference engine which constructs low-dimensional data vectors called *features* in which the effect of damage is much more visible. An example of a damage-sensitive feature vector often used in vibration-based SHM would be a set of the natural frequencies or resonance frequencies of the structure of interest. Natural and resonance frequencies are functions of the structural stiffness and will (usually) decrease when damage - such as a fatigue crack - causes a local reduction in stiffness. Determining natural frequencies from the raw time data is one example of *feature extraction* as it is referred to in the context of pattern recognition or machine learning [1]. Once damage-sensitive features have been determined, the SHM inference engine can proceed to an analysis which provides diagnostic and prognostic information about the health of the structure.

One of the major problems associated with SHM, is that features may change as a result of mechanisms other than damage and one does not usually wish to raise an alarm as a result of these benign changes. These other influences on the features will be referred to here as *confounding influences*; they most often arise in the context of engineering as the result of changes in the environment or operating conditions of the structure of interest. For the bridges discussed in this paper, ambient temperature is an environmental variable which strongly affects the SHM features, while traffic loading is an equally important operational influence. If natural frequencies are to be used as features for SHM, it has long been known that variations in the frequencies due to temperature changes can mask variations due to damage [2]. In order to implement damage detection by detecting changes in features, one must clearly produce features that are sensitive to damage but insensitive to environmental and operational variations, or alternatively, one must project out from the features the influence of the benign variations. This process is commonly referred to in the SHM literature as *data normalisation*; various techniques can be applied and a good, fairly recent, survey of the field can be found in [3].

Among the techniques available for data normalisation, one of the simplest is a regression-based approach. This relies on the availability of measurements of the environmental or operational variables of interest. When the features for SHM are based on the dynamics of the structure – as in vibration-based SHM – the response variables almost always change on a much shorter time-scale than the confounding influences. For example, accelerations measured on a bridge will have frequencies associated with tens of Hertz, while cycles of variation associated with temperature or traffic will be on scales of hours or more. This means that time histories acquired over hours or days will show their main variation as a result of the confounding influences, with the dynamical behaviour superimposed as a form of high-frequency 'noise'. Fitting a regression model to such data with the environmental or operational variables as the independent variables will then capture only the dependence on the confounding influences, predictions from this model can then be subtracted from subsequent data, with the remaining residual (hopefully) sensitive *only* to damage. Regression models used in this context are often called *response surface models* and can vary in sophistication from simple polynomials [4], to state-of-the-art structures derived from modern machine learning theory like artificial neural networks and support vector machines [5,6]; examples from both ends of the spectrum will be presented in this paper. Complications can arise if the confounding influences cause discontinuous changes in the features as the ambient variables change, for example if polynomial models are selected, discontinuous behaviour may force the choice of very high-order polynomials with the result that very many coefficients need to be estimated. If the response surface models have the capability to *switch* between simple (e.g. linear) submodels, the number of parameters for estimation from the data can be much smaller, such models are often referred to as *parsimonious*. Parsimonious models are always selected where possible as they require less training data for their estimation problem, and data from structures in engineering SHM problems, particularly data corresponding to damage states, can sometimes be in short supply. In the machine learning context, parsimonious models are desirable because they are less prone to overfitting [7].

As mentioned above, when nonlinear models are required, there are numerous options for the model structure. The structure chosen here is the *Gaussian Process* (GP) [8]; this represents a powerful nonparametric regression technique which has been developed considerably within the machine learning community in the last 10–15 years. Advantages of the GP approach include a natural Bayesian framework for analysis and the automatic availability of confidence intervals for model predictions. In fact, Gaussian processes have a pedigree in terms of response surface modelling and sensitivity analysis [9], and the current authors have exploited this for their previous studies on engineering problems [10,11].

The approach to data normalisation discussed above and in the remainder of the paper can be referred to as a *subtraction* strategy. Another powerful approach can be based on the idea of *projection*, whereby the subspace of the feature space containing the confounding influences is identified and the features are projected onto the orthogonal complement of the corrupted subspace. The projection approach has various merits, including the property that one does not require measurements of the latent variables driving the confounding influences. The projection approach is not discussed further