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Estimating the Bias Associated with Inspectors in the Context of Visual Inspections on Infrastructures

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ABSTRACT: Visual inspection is one of the most common methods to collect data about the condition of infrastructures. The main disadvantage of visual inspections is attributed to the errors stemming from the inspectors' subjectivity. Recent developments have enable addressing the inspectors' uncertainty, while modelling the degradation based on visual inspection data. Specifically, the use of state-space models has allowed the estimation of the standard deviations of the errors associated with each inspector, while assuming the inspectors to be unbiased (i.e., zero mean). This paper proposes a modified approach that allows the estimation of the relative bias associated with each inspector. The predictive capacity of the new framework is verified using synthetic data, where the true values are known.

KEY WORDS: Inspector Bias; Visual Inspections; Bridge Degradation; Structural Health Monitoring.

1. INTRODUCTION

The aim of structural health monitoring (SHM) is to track and supervise the health state of infrastructures, so that it is possible to maintain their safety and structural integrity. Visual inspections are commonly employed to collect data, where inspectors go on-site to evaluate and record the condition of structural elements. The main limitations of visual inspections is the high variability due to the inspectors' subjectivity, which consequently affects the capacity to model the degradation using such data.

State-Space Models (SSM) have been applied successfully to model the degradation based on visual inspection data, while accounting for the inspectors uncertainty [2]. Nonetheless, the SSM framework assumes that the inspectors are unbiased by considering a zero-mean random variable for errors associated with each inspector.

In this paper, a modified SSM model is proposed in order to take into account the relative bias associate with each inspector. The performance of the new SSM model is verified using synthetic data, where the true states and parameters values are known.

1.1. Notations

The SHM database is composed of a set of $\mathtt{B}$ bridges $\mathcal{B} = \{b_1, b_2, ..., b_{\mathtt{B}}\}$, where each bridges b_j is composed of a set of structural elements $\mathcal{E} = \{e_1^j, e_2^j, ..., e_{\mathtt{E}_j}^j\}$. At a given year t, for a given element, the visual inspection is performed by an inspector $I_i \in \{I_1, I_2, ..., I_{\mathtt{I}}\}$. The inspector grades the condition $\tilde{y}$ of the elements on a scale from l to u. Typically, the frequency of inspections for a bridge is about two years [5].

2. MODELLING STRUCTURAL DEGRADATION

2.1. State-Space Model

To estimate the degradation condition of a structural element at any time t, the SSM framework relies on a transition model and an observation model [2]. Knowing the degradation state $\boldsymbol{x}_{t-1,p}^j$ at time $t-1$, the transition model predicts the degradation state $\boldsymbol{x}_{t-1,p}^j$ at time t using equation 1,

$$\underbrace{\begin{bmatrix} x_t \\ \dot{x}_t \\ \ddot{x}_t \end{bmatrix}}_{\boldsymbol{x}_{t,p}^j} = \underbrace{\begin{bmatrix} 1 & \Delta t & \frac{\Delta t^2}{2} \\ 0 & 1 & \Delta t \\ 0 & 0 & 1 \end{bmatrix}}_{\boldsymbol{A}^{ki}} \underbrace{\begin{bmatrix} x_{t-1} \\ \dot{x}_{t-1} \\ \ddot{x}_{t-1} \end{bmatrix}}_{\boldsymbol{x}_{t-1,p}^j} + \underbrace{\begin{bmatrix} w_t \\ \dot{w}_t \\ \ddot{w}_t \end{bmatrix}}_{\boldsymbol{w}_t^{ki}}, \tag{1}$$

where Δt is the time step duration and $\boldsymbol{w}_t^{ki}$ represents the process error. The relation between the inspection data $y_{t,p}^j$ and the hidden state $\boldsymbol{x}_{t-1,p}^j$ is defined by the observation model in equation 2,

$$\overbrace{y_{t,p}^j = \boldsymbol{C}^{ki}\boldsymbol{x}_{t,p}^j + v_t}^{\text{observation model}}, \quad \underbrace{v_t : V \sim \mathcal{N}(v; 0, \sigma_V^2(I_i))}_{\text{observation error}}, \tag{2}$$

where $\boldsymbol{C}^{ki} = [1,\ 0,\ 0]$ is the observation vector, v_t the observation error associated with the i-th inspector who has performed the inspection of the element e_p^j at time t. The estimation of the hidden state is performed using the Kalman Filter (KF) [4] and the RTS Kalman smoother [6].

2.2. Model parameter estimation

The SSM model relies on the set of parameters $\boldsymbol{\theta} = \{\sigma_V(I_{1:\mathtt{I}}), \sigma_W, \boldsymbol{\theta}_0\}$, where $\boldsymbol{\theta}_0$ is the set of parameters characterizing the initial state of the degradation model. The estimation of model parameters is done using the *Maximum Likelihood Estimate* (MLE) approach [1], which depends on maximizing the log-likelihood of the joint prior probability of observation given the parameters defined in Equation 3,

$$\mathcal{L}(\boldsymbol{\theta}) = \sum_{j=1}^{\mathtt{B}} \sum_{p=1}^{\mathtt{E}_j} \sum_{t=1}^{\mathtt{T}_p} \ln f(y_{t,p}^j | y_{1:t-1,p}^j, \boldsymbol{\theta}). \tag{3}$$

It is possible to identify $\boldsymbol{\theta}^*$ that maximizes $\mathcal{L}(\boldsymbol{\theta})$ by using a Newton-Raphson (NR) algorithm, a gradient-based optimization method [3].

3. ESTIMATING THE INSPECTOR RELATIVE BIAS

In order to take into account the relative biases of each inspectors, the observation error v_t defined in Equation 2 is modified, such that,

$$v_t : V \sim \mathcal{N}(v; \mu_V(I_i), \sigma_V^2(I_i)),$$

where $\mu_V(I_i)$ is the relative bias of inspector I_i, which is considered as an additional model parameter. It should be noted that the world *relative* here implies that while the inspectors could overestimate or underestimate the true condition, the expected value for the biases from all inspectors is zero, $\mathbb{E}[\boldsymbol{\mu}_{V(1:\mathtt{I})}] = 0$. The estimation for the bias parameters $\mu_V(I_i)$ for all inspectors is done using the Newton-Raphson (NR) algorithm. Moreover, all the inspectors' bias values are assumed initially to be $\mu_V(I_i)_{t=0} = 0$, and are maintained within the bounds $-u < \mu_V(I_i) < u$.

4. CASE STUDY

In order to verify the framework's capacity to estimate the bias, a synthetic dataset is generated with $\mathtt{E} = 18000$ structural elements and $\mathtt{I} = 250$ synthetic inspectors. The synthetic dataset is generated according to the concepts defined in the work of Hamida and Goulet [1, 2], and by considering a non-zero true bias for each inspector, such that, $\mu_V(I_i) \sim \mathcal{U}(-4, 4)$.

The estimation for inspectors parameters for the synthetic data is shown in Figure 1. From Figure 1a, the alignment with the diagonal line confirms the capacity to estimate the relative bias $\mu(V_i)$, compared to the true synthetic inspector bias values. Nonetheless, it is also noticeable that there is a deviation in the positive domain for the estimates, this can be attributed to the complexity of the problem, as well as the fact that the degradation model is monotonic. Moreover, from Figure 1b, the addition of the biases in the framework does not affect the estimation of the standard deviations $\sigma(V_i)$.

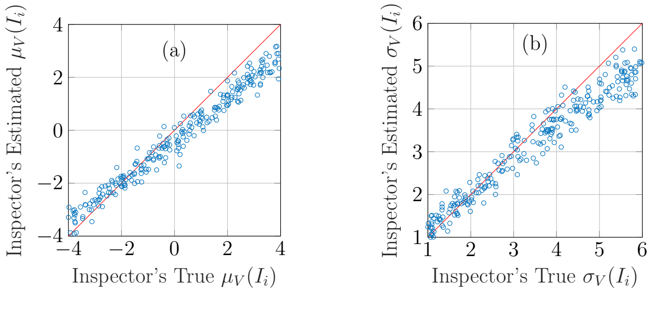

Figure 1: Estimation results for the synthetic inspectors' uncertainty parameters versus their true values.

In order to assess the performance of the degradation model with the new parameters, the predictive capacity of the SSM model is examined by assessing the average forecast error. In this assessment, the average forecast error is examined for degradation condition and speed of $\mathtt{E} = 500$ synthetic structural elements, over the period of 10 years. Figure 2 shows the analyses results for the degradation condition (in Figure 2a) and the degradation speed (in Figure 2b). In this figure, the results are shown for two SSM models, 1) the SSM model with the new bias parameters $\mu_V(I_i)$ (represented by the red line), and 2) the SSM model with unbiased inspectors $\mu_V(I_i) = 0$ (shown in the dashed line). From Figure 2, the average forecast error for both the condition and the speed are smaller for the SSM framework that accounts for the inspector bias (in red line), compared with SSM framework with $\mu_V(I_i) = 0$. The results of the analyses confirm that the addition of the bias has improved the overall predictive capacity of the SSM degradation model.

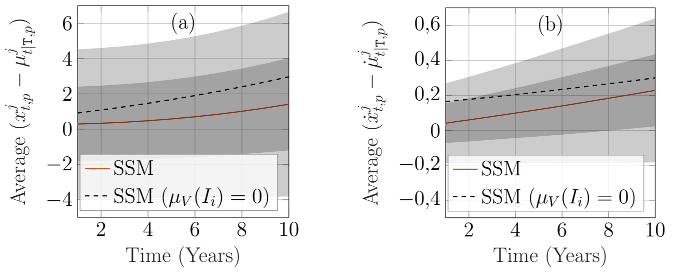

Figure 2: Average forecast error for the degradation condition and speed of $\mathtt{E} = 500$ *elements for the SSM framework with bias (in red line) and without bias (in black dashed line)*

5. CONCLUSION

In this study, a modified SSM degradation model is proposed to take into account the bias associated with each inspector. The modifications include considering the relative bias associated with each inspector as an additional model parameter, to be estimated within the parameter estimation framework. The analyses with synthetic data have verified the capacity of the new framework to effectively estimate the relative biases, which coincides with improvements in the overall predictive capacity of the degradation model.

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