Degradation Model Updating for Failure Prognostics Using a Sequential Likelihood-Free Bayesian Inference Method and Video Monitoring Data

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ABSTRACT

Structural systems are inevitably subject to degradation that evolves progressively over time. Developing a degradation model to capture the physics of damage evolution is essential for failure prognostics, i.e., remaining useful life (RUL) prediction, to enable individualized predictive maintenance. Due to the lack of run-to-failure data for large structural systems and natural variability across physical systems, uncertainty is inherent in the degradation model even if a degradation model can be constructed based on the physics of a certain damage mechanism. It is therefore necessary to update the degradation model over time based on measurements of quantities that are directly measurable. With the development of sensing and image processing techniques, it is possible to derive structural strain response from videos, which overcomes the limitations of the cumbersome and costly deployment of conventional contact sensors. While the strain video monitoring data provide rich information for structural health monitoring, the usage of this information for degradation model updating is challenging due to the implicit connection between the degradation model parameters and strain video monitoring data and the highly complicated model architectures. This research proposes a novel sequential Bayesian model updating framework for a degradation model using a likelihood-free Bayesian inference method and strain video monitoring data. In the proposed framework, strain video monitoring data are first compressed into low-dimensional latent time-series features using a convolutional autoencoder. Subsequently, a likelihood-free Bayesian inference method is employed to update the degradation model using a given time duration of the monitoring data. To enable continuous monitoring and model updating over a long time period, a sequential

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Bayesian model updating scheme is developed. Based on the updated degradation model, failure prognostics are performed sequentially and the associated uncertainty on RUL estimation is also quantified. The application of the developed framework to a miter gate structure demonstrates the efficacy of the proposed framework.
Keywords: Remaining useful life; Degradation model; Likelihood-free Bayesian inference; Conditional invertible neural network

1. INTRODUCTION

The degradation phenomenon, characterized by the accumulation of damage over time, is typically irreversible. It is essential to develop degradation models that facilitate us to comprehend the degradation behavior of a system [1]. For large-scale and complex structures, physical or hybrid degradation models are more appropriate than pure data-driven models for failure prognostics, given a scarcity of historical monitoring data. Although physical or hybrid models are formulated based on physical principles that describe the degradation behavior, there are still several limitations. Degradation modeling usually involves many assumptions and simplifications due to complex and multifaceted degradation mechanisms. The over-simplified models may fail to capture the complete physics of systems being modeled, thereby resulting in inaccurate failure prognostics. In addition, the availability of curated failure data is not always guaranteed due to the inherent unobservability of certain types of damage.

To improve the accuracy and reliability of degradation model and further better predict failure condition, the simplified degradation model needs to be updated. Bayesian inference provides a principled framework for degradation model updating and received considerable attentions. Although substantial studies can perform a fairly good failure prognostics, the evaluation of likelihood function in Bayesian inference is required. However, the likelihood function is usually intractable and unavailable in a close-form due to degradation model complexity [2].

Recently, neural network-based Bayesian inference (NNBI) has received many interests , as it takes advantage of Bayes theorem and deep learning and realizes the amortized inference. Radev et al. [3] employed BayesFlow for parameter estimation given multidimensional observations, which has two complementary neural networks trained jointly: summary network and inference network through conditional invertible neural network (cINN) for the true posterior approximation. Later, Zeng et al. [2] explored applicability of NNBI in the area of structural health monitoring (SHM), especially for probabilistic damage detection in an 18-story shear frame and a large-scale concrete building. The theory of NNBI is funded on normalization flow that has bijective mapping between complex and irregular distributions and multivariate Gaussian distribution. More importantly, the method realizes amortized inference encompassing an upfront training phase with much computational efforts which can be executed offline, and an inference phase that completes nearly instant parameter estimation without losing accuracy. However, some challenges in NNBI still remains to be addressed. The scope of NNBI is limited to inferring parameters based on new observations with measurement lengths that do not surpass those of the training phase. Consequently, its practical applicability is often hindered in scenarios where data is continuously recorded over an extended period, such as in long-term SHM.

In addition to a proper methodology for Bayesian inference, the data type also plays a vital role in accuracy and reliability of model updating. Over the past few years, computer vision-based technique has emerged as a promising solution for remote measurement of structural responses. The use of video imaging techniques allows to monitor the target structures and facilitate the extraction of responses, such as displacements without the need for physical contact [4]. The application of remote sensing techniques through video imaging provides a time-efficient and cost-effective alternative to the installation of physically connected sensors. However, most research studies have primarily focused on processing video images solely for displacement responses. Model updating and damage detection are then performed based on the extracted displacements and operational modal analysis [5]. Furthermore, establishing a correlation between video images and degradation models is challenging due to the complexity of the model and the large size of the image data.

Motivated by aforementioned challenges, this paper proposes a novel Recursive likelihood-free Bayesian inference (RELFBI) method for degradation model updating using monitored video images. A convolutional autoencoder (CAE) model is first trained using the synthetic video images, which compresses images into low-dimensional latent space representation. Subsequently, two complementary neural networks, namely a summary network and a cINN, are jointly trained using the compressed images. Upon training completion, the new video images collected from field test are compressed by the trained CAE model. Finally, a novel recursive model updating strategy is proposed to update the uncertain model parameters in a recursive manner. The posteriors keep being updated with the incorporation of newly acquired images until all image data is fully utilized. The developed framework is applied to a real-world engineering structure, a miter gate, for the damage prognostic of gap length growth and RUL prediction.

The reminder of this paper is organized as follows. Section 2 provides the details of proposed recursive likelihood-free Bayesian inference framework. Section 3 is dedicated to a miter gate to demonstrate the efficacy and applicability of proposed framework for failure prognostics and RUL estimate. Finally, conclusions and contributions are discussed in Section 4.

2. A RECURSIVE LIKELIHOOD-FREE BAYESIAN INFERENCE (ReLFBI) METHOD FOR DEGRADATION MODEL UPDATING

2.1. Degradation Model of a Miter Gate

In this study, our research will center on a miter gate to undertake degradation model updating and failure prognostics. The damage of interest is the contact loss between gate and supporting wall, which is quantified by gap length, as shown in Figure. 1. The simplified degradation model of a miter gate is developed based on state equation and observation equation.

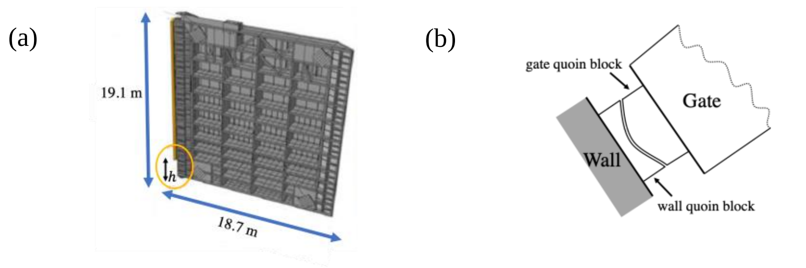

Figure. 1. Illustration of a miter gate: (a) gap at the bottom; (b) quoin block

The state equation is given by $h_k = h_{k-1} + \exp(\sigma_k U_k) Q_K a_{k-1}^{\beta_k}$, where h_k and h_{k-1} are state variables at time step t_k and t_{k-1}, respectively. U_k is a standard normal random variable. a_{k-1} is the unobserved response at time step t_{k-1}. σ_k, Q_k, and β_k are degradation model parameters. This study assumes that the number of degradation stages is three, leading to 13 variables in degradation model of a miter gate to represent the variation of gap length.

The observation (strain response) equation is given by $\mathbf{s}_i^e = [\mathbf{s}_{1k}, \cdots, \mathbf{s}_{N_d k}] = g_{strain}\left(h_k, \mathbf{x}_k\right) + \epsilon_s$, where $\mathbf{s}_{ik}$ represent the strain response at spatial location $\mathbf{d}_i, i = 1, \cdots, N_d$ and time t_k. ϵ_s denote measurement noise that is assumed as Gaussian random variables. $g_{strain}\left(h_k, \mathbf{x}_k\right)$ is a model to predict strain measurements at sensor locations. In this model, the latent variable h, e.g., gap length, and controllable variables $\mathbf{x}$, are selected as the inputs. Specifically, $\mathbf{x}_k = \left[x_{k1}, x_{k2}, x_{k3}, x_{k4}\right]$, in which x_{k1} and x_{k2} are respectively upstream and downstream water levels at time step t_k. x_{k3} and x_{k4} are temperatures at water surface and under the water, respectively.

There are two main challenges in updating simplified degradation model of miter gates to enhance the prognostic accuracy: (1) traditional NNBI only works on the data length of new observations not exceeding that of the simulation data used to train the model; (2) video images possessing high resolution typically exhibit high dimensionality, which entails a considerable computational burden. In next sections, we will elaborately explain how to address these challenges.

2.2. Convolutional Autoencoder for Data Compression of the Image Monitoring Data

To address the first challenge of high-dimensional strain video images, the convolutional autoencoder (CAE) is employed to transform the high-dimensional video image data into low-dimensional data to facilitate degradation model updating. CAE is an unsupervised machine learning algorithm aiming at encoding input data into a lower-dimensional representation and then decode it back to the original input shape. As illustrated in Figure. 2, the basic structure of an autoencoder consists of an encoder network and a decoder network. The input data, e.g., video images, is fed into the encoder, which learns to map it to a compressed representation. The compressed representation is then passed to the decoder, which learns to map it back to the original input shape. The output of the decoder is the reconstructed image data, which should ideally be as close as possible to the original input image under a perfect convergence in training. The size in the compressed representation layer is typically smaller than those in the input and output layers. This compressed representation can be used for tasks such as feature extraction and image compression.

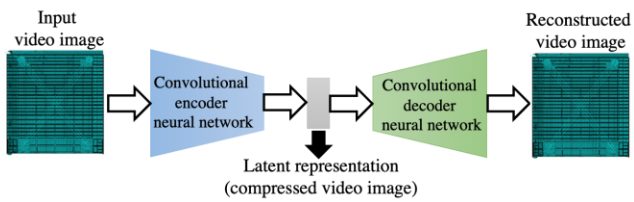

Figure. 2. Concept illustration of CAE

2.3. Neural Network-based Bayesian Inference Using cINN

When monitored strain video images are processed to low-dimensional ones by convolutional encoder, the NNBI is implemented to estimate the posteriors of degradation model parameters using compressed image data $\xi_{o,1:N_o}$, where N_o is the length of observed video. The basic idea of NNBI is normalizing flow that achieves bidirectional mappings between a non-Gaussian distribution and a multivariate Gaussian distribution. In this study, a variant of the cINN developed in Ref. [6] is employed. The overall network model consists of two complementary deep neural networks that are jointly trained, namely, A summary network which is used to reduce the dimension and capture the maximally informative features for inference, and an inference network implemented by a cINN with a sequence of cACLs to achieve the invertible transformation.

Denote parameters of the two networks as $\boldsymbol{\phi} = \{\boldsymbol{\phi}_s, \boldsymbol{\phi}_c\}$, where $\boldsymbol{\phi}_s$ and $\boldsymbol{\phi}_c$ are parameters in summary network and in cINN, respectively, degradation model parameters as $\boldsymbol{\theta}$. For given compressed observation $\xi_{o,1:N_o}$, the optimal $\hat{\boldsymbol{\phi}}$ are identified by minimizing the Kullback-Leibler (KL) divergence between the target $f_{\boldsymbol{\theta}|\xi}(\boldsymbol{\theta} \mid \xi_{o,1:N_o})$ and the approximated posterior $p_{\boldsymbol{\phi}}\left(\boldsymbol{\theta} \mid \xi_{o,1:N_o}\right)$ as $\hat{\boldsymbol{\phi}} = \underset{\boldsymbol{\phi}}{\operatorname{argmin}}\, \mathrm{E}_{f\left(\xi_{o,1:N_o}\right)}\left[\mathrm{KL}\left[f_{\boldsymbol{\theta}|\xi}(\boldsymbol{\theta} \mid \xi_{o,1:N_o}) \,\|\, p_{\boldsymbol{\phi}}\left(\boldsymbol{\theta} \mid \xi_{o,1:N_o}\right)\right]\right]$, where $\mathrm{KL}[\cdot]$ is the KL divergence and $\mathrm{E}(\cdot)$ is the expectation operator. For comprehensive derivations, one can refer to Ref. [6].

2.4. Recursive Likelihood-free Bayesian Inference

To overcome the second challenge described in Sec. 2.1, this study proposes a novel recursive updating strategy named ReLFBI. The framework starts with the phase of offline model training, which consists of the synthetic data generation from degradation model, the training of the CAE model, and training of a cINN model.

Finally, we can use all trained neural network models to perform online recursive model updating over a long period.

In the phase of online model updating, the new video images are firstly compressed by the trained autoencoder. Assume the first two consecutive segments after image compression with the same length, $\boldsymbol{\chi}_1 \triangleq \{\boldsymbol{\xi}_{o,1}, \boldsymbol{\xi}_{o,2}, \cdots, \boldsymbol{\xi}_{o,N_T}\}$, $\boldsymbol{\chi}_2 \triangleq \{\boldsymbol{\xi}_{o,N_T+1}, \boldsymbol{\xi}_{o,N_T+2}, \cdots, \boldsymbol{\xi}_{o,2N_T}\}$. The goal is to estimate the posterior distribution $f(\boldsymbol{\theta} | \boldsymbol{\chi}_1, \boldsymbol{\chi}_2)$. We can approximate $f(\boldsymbol{\theta} | \boldsymbol{\chi}_1, \boldsymbol{\chi}_2)$ as

$$f(\boldsymbol{\theta} | \boldsymbol{\chi}_1, \boldsymbol{\chi}_2) = \frac{f(\boldsymbol{\chi}_1, \boldsymbol{\chi}_2 | \boldsymbol{\theta}) f(\boldsymbol{\theta})}{\int f(\boldsymbol{\chi}_1, \boldsymbol{\chi}_2 | \boldsymbol{\theta}) f(\boldsymbol{\theta}) \mathbf{d}\boldsymbol{\theta}} \propto f(\boldsymbol{\chi}_2 | \boldsymbol{\theta}) f(\boldsymbol{\theta} | \boldsymbol{\chi}_1), \tag{1}$$

where the term of $f(\boldsymbol{\theta} | \boldsymbol{\chi}_1)$ can be estimated by trained summary and cINN networks. On the other hand, based on uniform prior, we have $f(\boldsymbol{\theta} | \boldsymbol{\chi}_2) \propto f(\boldsymbol{\chi}_2 | \boldsymbol{\theta}) C \Rightarrow f(\boldsymbol{\chi}_2 | \boldsymbol{\theta}) \propto f^C(\boldsymbol{\theta} | \boldsymbol{\chi}_2)$. Eq. (1) can be rewritten as $f(\boldsymbol{\theta} | \boldsymbol{\chi}_1, \boldsymbol{\chi}_2) \propto f^C(\boldsymbol{\theta} | \boldsymbol{\chi}_2) f(\boldsymbol{\theta} | \boldsymbol{\chi}_1)$. In this study, the particle filter method and Gaussian mixture model (GMM) are used to combine the samples $\boldsymbol{\theta}_{\chi_2}$ from $f^C(\boldsymbol{\theta} | \boldsymbol{\chi}_2)$ and samples $\boldsymbol{\theta}_{\chi_1}$ from $f(\boldsymbol{\theta} | \boldsymbol{\chi}_1)$. More specifically, we first approximate $f(\boldsymbol{\theta} | \boldsymbol{\chi}_1)$ using GMM based on samples $\boldsymbol{\theta}_{\chi_1}$. The samples $\boldsymbol{\theta}_{\chi_2}$ are then plugged into the GMM model to calculate likelihood function. The weights of samples $\boldsymbol{\theta}_{\chi_2}$ can be estimated using the GMM calculations. Finally, the posterior distribution $f(\boldsymbol{\theta} | \boldsymbol{\chi}_1, \boldsymbol{\chi}_2)$ can be approximated through resampling using particle filter. We can also extend the above proposed framework to a more generalized case, such as multiple image segments rather than two segments. The above procedures are implemented recursively over time and thereby enable long-term monitoring with a large amount of video image data.

3. APPLICATION EXAMPLE: MITER GATE

In this study, we selected three variables from 13 variables in degradation model of miter gate in Sec. 2.1 through sensitivity analysis. Thus, three parameters are used as the to-be-updated model parameters and denoted as $\theta_1, \theta_2, \theta_3$ for the sake of brevity, others are fixed at the nominal values. In the proposed framework, non-informative uniform prior distributions $U[0.9,1.1]$ are used for the three model parameters. Specifically, the model parameters are defined as the ratio of the updated value to the nominal value. The Latin Hypercube Sampling method is utilized to generate 700 sets of model parameters, resulting in 700 video outputs. Each video comprises 1800 images over 1800-time steps. Each time step represents one-third of a month, resulting in a total of 600-month measurement duration. We also down-sampled the 1800 images to 450 images for each video. Moreover, each image has a dimension of 750 × 750 × 3. Consequently, a total of 315,000 images are used to train autoencoder. Additionally, 100 sets of test data with 45,000 images are generated for the validation.

The trained encoder network is then employed to pre-process each image. In this regard, the compressed image size is designed to be 500. Figures. 3 (a) and (b) presents the comparison between original and reconstructed images recorded at different time. It is evident that the reconstructed image graphically exhibits a satisfactory agreement with the original image. We then partitioned compressed image into five segments based on the recording time interval. Thus, each time interval has 90 images. The cINN-based Bayesian inference model developed for 120 months is employed to approximate the posteriors using 20,000 samples. Figure. 4 shows that posterior distribution still concentrates on a wide region for many parameters and model yields disparity between the estimated and true values, which can be explained by 120-month image data are insufficient to train model accurately.

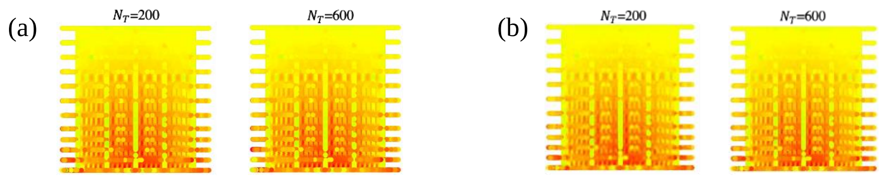

Figure. 3. Results of convolutional autoencoder: (a) original image; (b) reconstructed image;

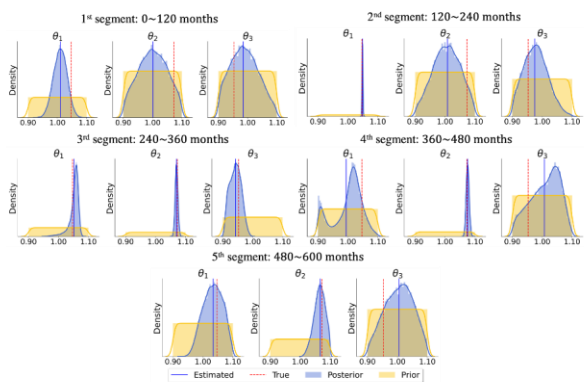

Figure. 4. Estimated posteriors for given five segments

Finally, the proposed ReLFBI is applied to perform recursive model updating. The results of the recursive model updating process are presented in Figure. 5. It is observed that the posterior mean obtained via ReLFBI exhibits a rapid convergence towards the ground truth. Conversely, the outcomes derived from single segment display significant divergence from the true values. Moreover, the results demonstrate that uncertainty gradually decreases with an increase in the recursive updating stage, as more measurement information is incorporated in the model, thus providing higher confidence in the predictions.

The model parameters estimated by ReLFBI are next used for failure prognostics, e.g., the RUL estimation. Figure. 6 displays the estimated and true RUL . In Figure. 6, the error bar indicates the 95% confidence interval. As observed, the estimated RUL for each of the five stages aligns closely with the true counterparts. Following 600 months of service, the RUL of the miter gate drops to zero, indicating a complete failure and the inability to function effectively. The uncertainty associated with the RUL estimates tends to decrease over time.

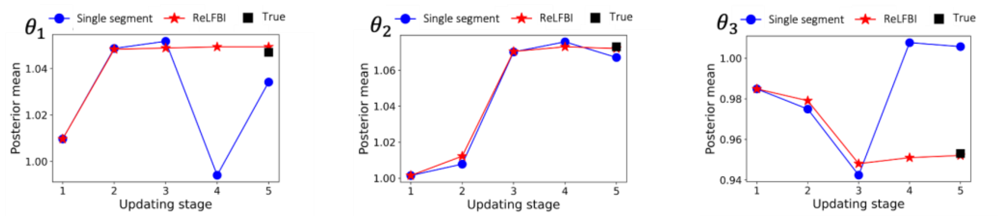

Figure. 5. Five-stage recursive model updating

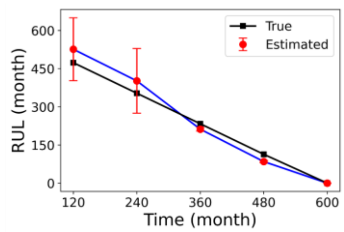

Figure. 6. RUL estimation over time

4. CONCLUSION

This work proposes a novel ReLFBI method, a recursive model updating framework, for degradation model using neural network-enabled Bayesian inference and continuously monitored video images. The goal is to improve the accuracy of model prediction and failure prognostics for degradation model, such as miter gate structure. In summary, the proposed ReLFBI framework represents a viable solution for addressing the challenges associated with model updating and failure prognostics using continuously monitored video images.

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