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ISBN
9783031054044

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Publication Date
2023

DOI
10.1007/978-3-031-05405-1_13

Peer reviewed

Crack Diagnosis and Prognosis of Miter Gates Based on A Global-Local Model and Image Observations

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ABSTRACT
This paper proposes a hybrid crack estimation technique that utilizes digital images from cameras and physics-based simulations to perform online diagnosis and prognosis of miter gate. To fully capture the localized effect of the crack, a global-local coupled finite element (FE) model is first created. An iterative global-local (IGL) algorithm is then developed to provide increased accuracy over sub-modeling at the expense of increased computational cost. To replace the process of solving the complex local FE, a Gaussian process (GP) surrogate model is further constructed to increase the computational efficiency. By interpolating the nodal displacement values collected from the surface around the crack, another GP surrogate model is developed to generate synthetic images similar to that obtained from cameras. The results demonstrate that the proposed method is able to efficiently predict the parameters of the crack growth model as well as to estimate the true crack length.

Keywords: Miter gates, Global-local iteration, Surrogate model, Bayesian network, Structural health monitoring

INTRODUCTION

Miter gates play an important role in inland waterway systems by enabling cargo ships to pass different water elevations, particularly under low-water conditions. Among the multiple forms of damage resulting from the aging of these steel structures, fatigue cracks are one of the most commonly damages found after visual inspections. Therefore, a comprehensive crack estimation framework that integrates diagnostics and prognostics is highly desirable, especially when in-site inspection is highly subjective and labour-intensive. In this work, we develop a method to perform efficient online diagnosis and prognosis using Bayesian networks and high-fidelity FE models. Since localized cracks at the initial phase are hard to detect by the globally distributed strain gage, we construct a GP surrogate model to generate synthetic image-based measurements for inference.

IGL ALGORITHM

As shown in Fig. 1, the global FE model of miter gate built by 3D linear shell elements does not contain the crack and is only coarsely discretized around the crack. The local model is defined as a cruciform which shares a local boundary with the global model. The local model is divided into two parts. One is the crack-affected zone using the Abaqus XFEM 3d solid shells where the feature of interest, a crack, is explicitly represented. The other is the rest of the sub-structures which uses the 3D shell elements. The global displacement around local boundary solving from global model is imposed as the boundary conditions of the local model, and the local force along the boundary solving from the local model is applied back as a reaction to the global model. The IGL algorithm finds an accurate representation of the physics by iteratively updating the interaction between the coupled global and local models. Stress intensity factor (SIF) as the key parameter of fatigue crack growth modeling indicates the crack growth pattern. For each step, the range of SIF values ΔK in a loading cycle at the crack front tip along with the crack length are extracted through stress analysis. In this paper, the Paris' law is adopted as a commonly used crack growth model,

$$da/dN = c(\Delta K)^m$$

where c and m are the material coefficients of Paris' law, da is the crack length change at each time step, and da/dN is the fatigue crack growth for a load cycle N. In order to increase the computational efficiency for the IGL method, a surrogate model using Gaussian Process Regression (GPR) [1][2] is constructed to replace the non-linear behavior of the local domain.

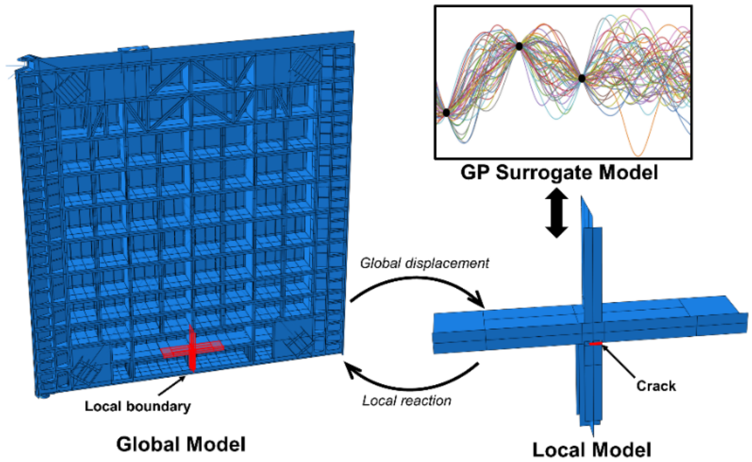

Figure 1. Illustrated IGL algorithm with global and local FE models of miter gate.

IMAGE-BASED MEASUREMENTS

Although FE analysis is capable of capturing the displacement for visualization, such computational-expensive model poses challenges to probabilistic analysis for diagnostics and prognostics. Given that the model needs to be executed thousands of times, an auxiliary surrogate model that is built to produce image-based observations, shown in Fig. 2. The images that come from a camera are consist of uniform square-like pixels, where the resolution of the images is determined by the side length of the pixels. By interpolating the Abaqus results into a uniform mapping, the function of "camera" can be fully learned.

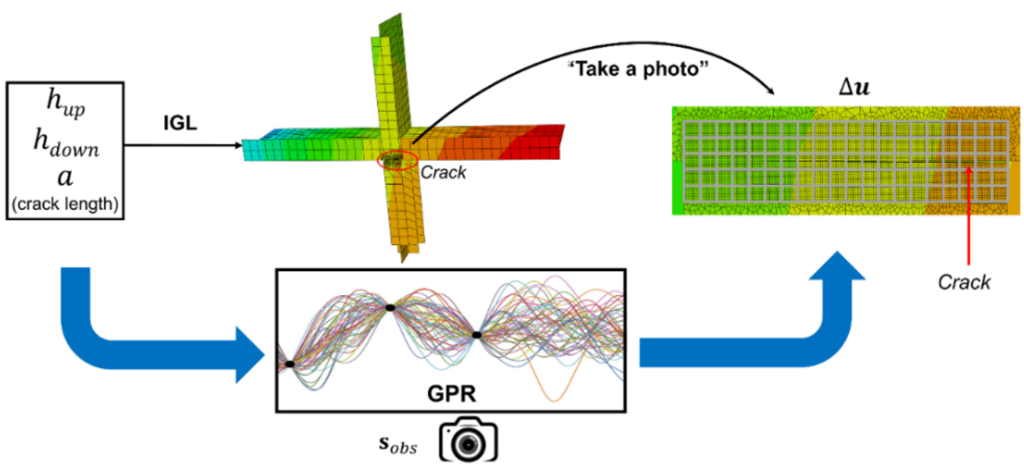

Figure 2. Auxiliary surrogate model to generate image-based measurements

ONLINE DIAGNOSIS AND PROGNOSIS

The diagnosis of the structures aims to detect and quantify the potential damage, which provides essential information on the current health state. Damage prognosis, in the meanwhile, extends the gathered information to predict the impact and the evolution of the damage, i.e., the remaining useful life (RUL) of the objective structures. Figure 3 illustrates the Bayesian network for online diagnosis where the h_{up} and h_{down} represents the upstream and downstream hydrostatic pressure applied on the global domain of the miter gate. The filtering process is composed of the crack evolution equation from IGL algorithm and observations from the auxiliary surrogate model that links the generated image-based measurements with the true system state [3]. The log-likelihood of the particles are first computed based on the observation data as follows,

$$\log L(\theta|x_1, \ \ldots, x_n) = \log\left(f(x_1, \ \ldots, x_n|\theta)\right) = \sum_{i=1}^{n\_obs} f(x_i|\theta).$$

and the weight of the particles is computed as,

$$weight_i = \frac{L(\theta_i)}{\sum_{i=1}^{N\_particle} L(\theta_i)}.$$

By repeated Monte Carlo (MC) sampling the particles based on their weights, the approximate conditional probability density function of the system state can be learned [4]. For each step of diagnosis, the RUL of the system can be predicted and updated by generating MC samples based on currently estimated parameters and crack length.

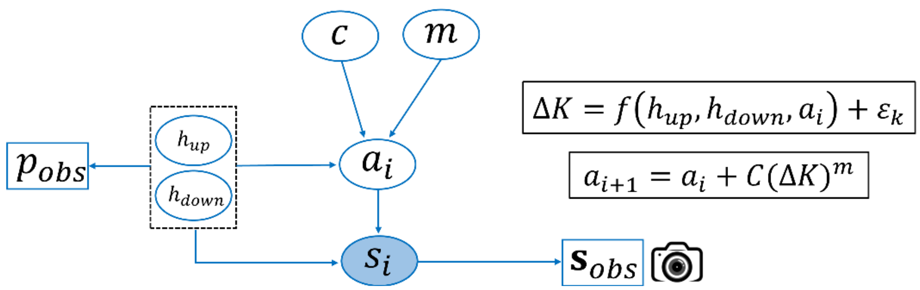

Figure 3. Bayesian network for online diagnosis

RESULTS

As shown in Fig. 4, both parameters of Paris' law converge to true values after certain time steps. Despite the large uncertainty at the beginning of the parameter updating, the proposed technique still managed to trace the crack growth pattern with high accuracy. The predicted RUL also converges to the true value within a few time steps. It is worth noted that even with a limited set of low-resolution pictures from the structure, the proposed framework can still accommodate great efficacy in performing crack diagnosis and prognosis.

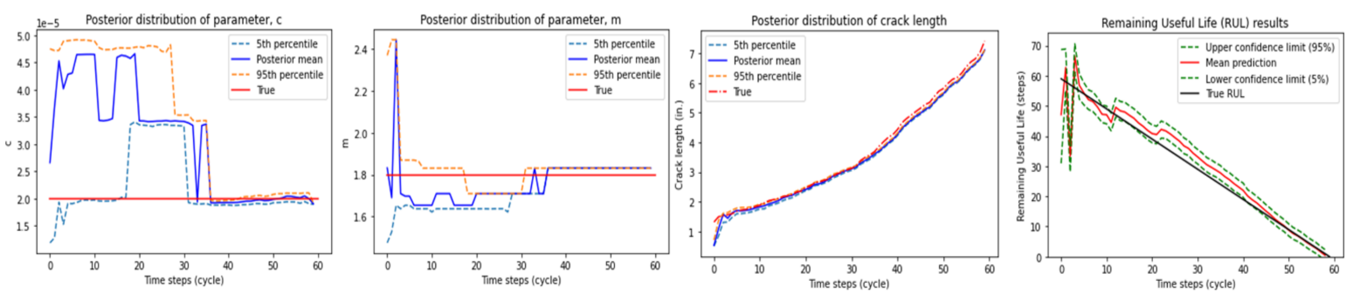

Figure 4. Online diagnosis and prognosis results

CONCLUSION

This work proposed a physics-based data-driven crack estimation framework with two novel advantages. An IGL-surrogate strategy is firstly developed which presents accurate physics of the feature of interest. In addition, the incorporated Bayesian network successfully predicts crack growth pattern and RUL of the component based on low-resolution images.

ACKNOWLEDGMENT

Funding for this work was provided by the United States Army Corps of Engineers through the U.S. Army Engineer Research and Development Center Research Cooperative Agreement W912HZ-17–2-0024.

REFERENCES

[1] Santner, Thomas J., et al. The design and analysis of computer experiments. Vol. 1. New York: Springer, 2003.
[2] Williams, Christopher K., and Carl Edward Rasmussen. Gaussian processes for machine learning. Vol. 2. No. 3. Cambridge, MA: MIT press, 2006.
[3] Corbetta, Matteo, et al. "Optimization of nonlinear, non-Gaussian Bayesian filtering for diagnosis and prognosis of monotonic degradation processes." Mechanical Systems and Signal Processing 104 (2018): 305-322.
[4] Arulampalam, M. Sanjeev, et al. "A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking." IEEE Transactions on signal processing 50.2 (2002): 174-188.