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A Kriging Surrogate Model for Structural Health Monitoring of Miter Gates in Navigation Locks

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ABSTRACT

Structural health monitoring (SHM) plays a significant role in monitoring the performance of the inland waterways civil infrastructure such as navigation locks. The United States has s $500B replacement value of its inland waterway infrastructure. Unexpected shutdowns of miter gates in navigation locks caused by any kind of damage produces tremendous economic loss, particularly if the shutdown is unplanned. Sensing is the first step in any process of damage detection strategy that collects data from sensing network. Lock gates are normally instrumented with strain gauges. A missing contact (or gap) between the concrete supporting wall and gate, one of the most common failure modes of lock gates, creates undesirable overloads and produces different levels of damage. An inverse model is needed to map the data extracted from the strain gauges to damage-sensitive features that are used to build degradation models and make decisions. An inverse Bayesian analysis is performed to identify damage by using strain gauge data. Although the posterior distribution estimations could provide probabilistic solutions to the damage identification, these models usually have high computational cost, and thus they are not suitable of performing real-time health monitoring. In this preliminary work, a Kriging or Gaussian process regression (GPR) inverse model is designed as a surrogate model of the finite element model of the Greenup lock miter gate, to map the strain gauge data to the damage size (i.e. gap length in miter gate contact). Hydrostatic loading scenarios governed by upstream and downstream heights with varying gap length are considered in the design of the Kriging model. Both training and testing data sets are predicted using the designed model. Overfitting problem caused by high nonlinear behavior of the data are solved. The results illustrated that Kriging, as a surrogate model, is a fairly reliable replacement to the computationally expensive inverse finite element model in damage identification. In addition, prediction performances using other Kriging models with different basic covariance functions and sizes of the training data set are compared.

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INTRODUCTION

The inland waterway transportation system in the US provides thousands of shippers a critical and safe way to fulfill their scheduled cargo deliveries [1–3]. In 2015, the U.S. Army Corps of Engineers (USACE) delivered more than $229 billion worth of cargo [4]. Navigation lock gates plays a critical role in this waterway transportation system as the closure due to malfunction of lock gates in these assets causes tremendous economic loss. As this infrastructure ages, more and more unexpected shutdowns are likely to happen. An efficient monitoring system is needed in urgent to keep track of the structural behaviors of these assets.

One of the most common damage scenarios in miter gates is the occurrence of gaps in the quoin block, which is an interface between the gate and the supporting wall [5]. When this gap size increases, the area which connects the gate to the supporting wall decreases, leading to stress redistribution that possibly exceeds design or performance limit states. For example, the cyclic nature of loading on the structure may cause fatigue failures in such high-stress zones [6]. Early prediction of gap development in miter gates informs the planning of repair strategies at the time of scheduled closure and to eliminate unscheduled (and much more costly) closures due to an unexpected failure of components of the structure. The most common loading scenario for miter gates is a hydrostatic pressure difference from the different water levels on both sides of the lock chamber. Hydrostatic loading at upstream and downstream will create an internal moment on vertical girders of a lock [7]. Therefore, distribution of stress and subsequently strains on the structure is a function of boundary conditions, hydrostatic loading, and temperature. Several navigation locks are instrumented using strain gauge sensors by USACE.

Structural health monitoring (SHM) can provide quantitative estimations of the performance condition of inland waterways infrastructure. To prevent the unscheduled shutdown of navigation locks in the United States, US Army Corps of Engineers (USACE) designed a discrete, indexed-based condition rating system to describe the components conditions of a navigation lock. Decision-makers are informed about repair and maintenance scenarios based on this simple rating system. [8, 9]. However, this monitoring system is highly dependent on the judgement of field engineers, which induces large variability in to the estimation results of the structure behavior. In a more efficient SHM system, inverse model is posed to directly relate the extracted measurement data to the damage parameters. For example, Bayesian Markov chain Monte Carlo (MCMC) inverse analysis approach is attractive because it provides posterior probabilistic estimations after informing priors and observed data [10]. Due to the complicated finite element model (FEM) in ABAQUS, and the Metroplis sampling algorithm [10], running ABAQUS from Python script through Theano [11] is a time-consuming process.

In this paper, we will build a Kriging method (or Gaussian process regression) to build a surrogate inverse model that maps the utilizing strain gauge data into gap size of in the quoin block. Here, we used only simulated data using a high resolution, previously-validated finite element model in ABAQUS. We also ignored the effect of the temperature on distribution of strains. We had to pre-run the ABAQUS model 3078 times and split data in to training data set and a testing data set. The Kriging model is learned from the training data set. We may observe the accuracy of model prediction by comparing to actual value that used for simulation. Besides, multiple covariance functions were applied and compared for their prediction performance on gap size. One of the challenges in this project is finding the best data size and best covariance functional form for training the surrogate model. We compared prediction performances from five covariance functions with the same training data size and also different strain data sizes with a same covariance function.

FINITE ELEMENT MODEL

A finite element (FE) model in ABAQUS (version 6.14-1), shown in Figure 2, is used to model the primary physics of the loaded miter gate, both for training and testing data generation. The damage (gap) is simulated by removing a part of the contact block which represents the connection in between gate and wall. The height of the removed part shows the intensity of the damage (gap length). Also, fifty-eight strain gauges are considered in the FE model similar to those sensors used in the real asset monitoring program. Figure 1 shows that the hydrostatic loading on the structure from both downstream and upstream.

In this work, we have three random parameters (i.e. gap length, upstream level, and downstream level of water). However, we only use the strain data to estimate gap length, so that changing the other two parameters are considered as variability in the this surrogate modeling problem.

KRIGING OR GAUSSIAN PROCESS REGRESSION

In any surrogate model construction problem, it is important to realize that the core of the problem is to build a mapping that transforms input vector **x** to output scalar y, as shown in Equation 1 .

$$y = f(\mathbf{x}) \tag{1}$$

To learn this mapping system, there are three main processes, including observing data, estimating the best model $\hat{f}$, and predicting output from input using $\hat{f}$.

In the data preparation process, model type and training data size selection are both important besides simulating strain values from randomly distributed gap lengths. Overfitting occurs when the model fits training data too fine and it also fits the error of training data set. As a results, the constructed model is only suitable for the selected training data set but low accuracy on testing data. In the learning process, we consider the model parameter estimation problem. The idea of maximum likelihood estimation (MLE) is implemented here. Given model parameters and model $\hat{f}$, we can calculate the probability of the data set that resulted from $\hat{f}$. Conversely, this is same as likelihood of the model parameters given the simulated data. The hyperparameters of the

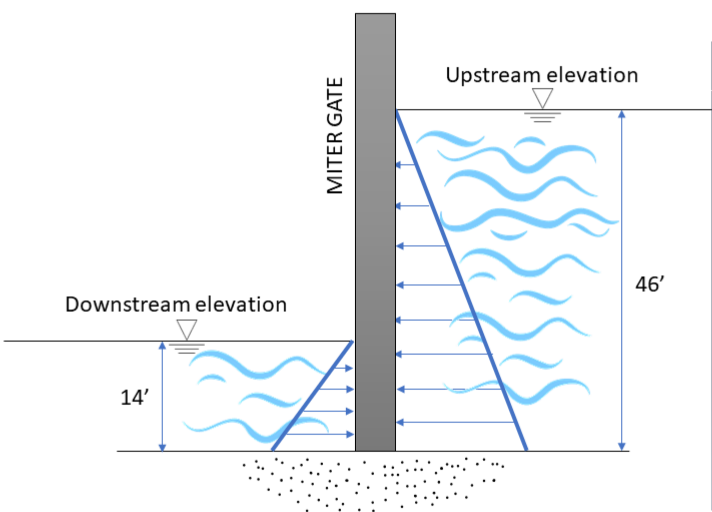

Figure 1. Hydrostatic loadings

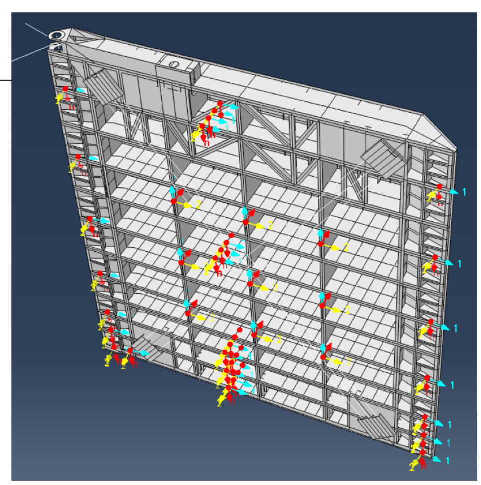
Figure 2. Gate and Fifty-eight strain gauges

TABLE I. PARAMETER DISTRIBUTIONS FOR SIMULATING DATA IN ABAQUS

Parameters of Interest	Distributions	units
Gap Length	$Uniform(0, 180)$	in
H_{down}	$Normal(\mu = 168, \sigma = 20)$	in
H_{up}	$Normal(\mu = 552, \sigma = 10)$	in

model are trained and optimized, so that it maximizes likelihood of observed data set. In model testing process, the testing data set should be selected randomly out of the entire simulated data set and should not contribute to learning process.

Perparing data and selecting kernel functions

To obtain the input **x** and output y in Equation 1, we performed 3078 runs in ABAQUS with parameter distributions shown in Table I. These parameter distributions are selected based on existing experts experiences on the parameters of interest in USACE. For example in a previously published work about damage detection in miter gates, a large gap was introduced as a gap with a length of 180 inches [5]. We used this to consider an upper bound for possible gap size. Also, we know the upstream and downstream levels of water are around 552 inches and 168 inches, respectively. We assumed a normal distribution for each of them with standard deviations of 10 inches and 20 inches, respectively.

Strain values from fifty-eight strain gauges are considered as input of surrogate model **x** and gap length y represents the output of the model. In this work, a covariance function $cor[Y(x^{(i)}), Y(x^{(j)})] = exp(-\sum_{j=1}^{k} \theta_j |x_j^{(i)} - x_j^{(l)}|^{p_j})$ is used to compare prediction performances with training data size 200, 300, 500, and 1000. Additionally, focusing on five sensors near the damage location, we compared performances of five different covariance functions, such as rational quadratic, radial-basis function (RBF), exponential sine squared, constant, and Matern, with same training data size of 66 percent of the entire data set.

Training mapping

In Gaussian process regression, any finite subset of outputs forms Gaussian random vector. The output at any single location has mean μ_0 and variance σ_0^2. The correlation function is used to compute correlations between every output Y_i and every other output Y_j. For example, the correlation function we used at first is shown in Equation 2

$$cor[Y(x^{(i)}), Y(x^{(j)})] = exp\left(t - \sum_{j=1}^{k} \theta_j |x_j^{(i)} - x_j^{(l)}|^{p_j}\right), \tag{2}$$

the corresponding correlation matrix of all the observed data

$$\Psi = \left(\begin{bmatrix} cor[Y(x^{(1)}), Y(x^{(1)})] & \dots & cor[Y(x^{(1)}), Y(x^{(n)})] \\ \vdots & \ddots & \vdots \\ cor[Y(x^{(n)}), Y(x^{(1)})] & \dots & cor[Y(x^{(n)}), Y(x^{(n)})] \end{bmatrix}\right), \tag{3}$$

and scale by σ to get covariance matrix

$$Cov(Y, Y) = \sigma^2 \Psi \tag{4}$$

The covariance between outputs depends on the absolute distance between their corresponding inputs. Outputs corresponding to relatively close inputs are positively correlated, while outputs corresponding to distant inputs are uncorrelated. θ_js and p_js are hyperparameters of the covariance function. The choices of θ_j and p_j affects the correlation. A low θ_j means there are high correlation between $Y(x_j)$s, and a high θ_j means there is a significant difference between inputs and induces low correlation.

Building a Kriging model is equal to choosing θ and p to maximize the likelihood of y. Ultimately, we hope that this will minimize the generalization error of the model. The likelihood function expressed in terms of the observed data,

$$L = \frac{1}{(2\pi\sigma^2)^{n/2}|\Psi|^2} exp\left[-\frac{(y-1\mu)^T\Psi^{-1}(y-1\mu)}{2\sigma^2}\right] \tag{5}$$

take the natural logarithm and use maximum likelihood estimates (MLEs) for μ and σ^2

$$\ln(L) \approx -\frac{n}{2}\ln(\hat{\sigma}^2) - \frac{1}{2}\ln(|\Psi|) \tag{6}$$

The term Ψ in Equation 6 is determined by hyperparamters θ and p. The problem becomes finding $\hat{\theta}$ and $\hat{p}$ that maximizes the equation. To achieve this, a numerical optimization technique named Particle swarm optimization (pso) was used to find the best result after global search.

Prediction

During the training process, we updated the hyperparameters that maximized the likelihood of observed y. In the Gaussian process, our observed y used for training and predicted $\hat{y}$ from new set of x are jointly Gaussian because they should have calculated from the same function f. In other words, the learned model (or hyperparamters) should maximize the likelihood of both observed data and the new prediction. Therefore, our data vector in training can be extended to $y_{new} = [y^T, \hat{y}]$ so our correlation matrix of observed and prediction data becomes

$$\Psi_{new} = \left(\begin{bmatrix}\Psi & \psi \\ \psi^T & 1\end{bmatrix}\right), \tag{7}$$

where ψ is the correlations between new prediction point $Y(x)$ and observed data used for training $[Y(x^{(1)}), \cdots, Y(x^{(n)})]$. The log likelihood after substituting $y_{new} = [y^T, \hat{y}]$,

$$\ln(L) \approx \left(\frac{-1}{2\hat{\sigma}^2(1-\psi^T\Psi^{-1}\psi)}\right)(\hat{y}-\hat{\mu})^2 + \left(\frac{\psi^T\Psi^{-1}(y-1\hat{\mu})}{\hat{\sigma}^2(1-\psi^T\Psi^{-1}\psi)}\right)(\hat{y}-\hat{\mu}). \tag{8}$$

The maximum likelihood, $\hat{y}$, is

$$\hat{y} = \hat{\mu} + \psi^T\Psi^{-1}(y-1\hat{\mu}). \tag{9}$$

In our work, we used the training model to predict both the training and testing input data from strain gauges. Different training and testing data sizes are compared.

RESULTS

Training size

There are total of 3078 realizations for training and testing of the Kriging model. Each realization presents a gap length in inches. Figure 3 illustrates gap prediction results using 1000, 500, 300, and 200 training samples, respectively. In all four figures, the x-axis represents realization number and the y-axis shows gap lengths for the corresponding realizations. The red dots in the subfigures demonstrate the actual values of gap lengths and the blue dots show the predicted

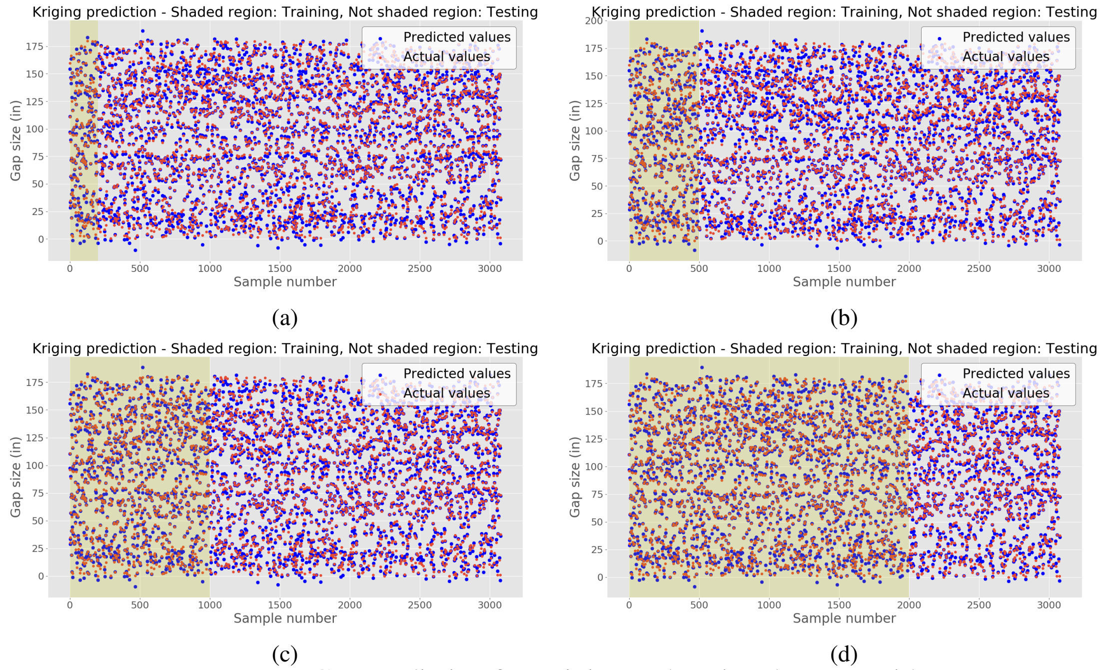

Figure 3. Gap prediction for training and testing data sets with
(a) 200 **(b)** 500 **(c)** 1000 **(d)** 2000 traning data sizes

TABLE II. MEAN OF MSE FOR THE TESTING RESULTS

Training points	Mean of MSE
200	0.46778
500	0.42695
1000	0.38742
2000	0.34916

gap length from the simulated strain data using our surrogate model. The shaded region represents training sample points while the unshaded region shows testing sample points. Since the entire 3078 realizations are generated randomly, it does not matter which subset of realizations we choose as our training set. For simplification, we just used first part of the data for training and considered the remaining part as the testing set.

From these subfigures (a) to (d), it can be seen that the Kriging models trained with different data sizes give fairly accurate predictions as the predicted values (blues dots) almost coincide with actual values (red dots) for both the training and testing data sets. To compare the prediction performances of using different training points, we computed the mean of the mean square error (MSE) of the testing values in Table II. The prediction accuracy of test data slightly increases when training data size increases from 200 to 2000. Training with larger number of sample points induces better prediction performance. However, there is a trade off between test accuracy and computation time.

Kernel functions

We are also interested in investigating the prediction performances using different kernel (covariance) functions. For simplification, we considered data set only from 5 strain gauges that are close to the damaged block. Also, for the purpose of illustration, we only used 200 total realization points for training and testing just in order to explore the prediction accuracy of

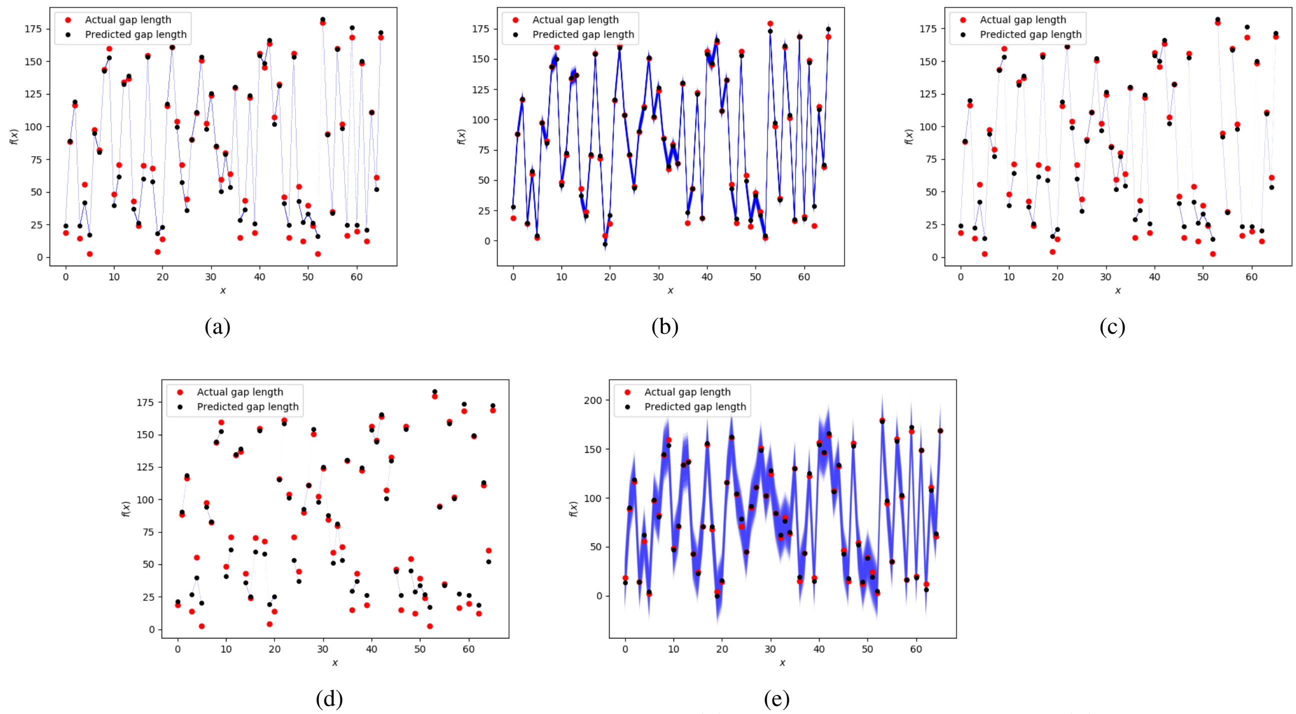

Figure 4. Gap prediction for test data with kernel functions **(a)** radial-basis function (RBF) **(b)** rational quadratic **(c)** exponiential sine squared **(d)** constant **(e)** Matern

different kernels. We used 66 percent of the total data for training the model and the remaining 33 percent data for testing. 95 percent confidence intervals and mean values of standard deviation of the predictions are both analyzed in this work for comparison. Figure 4 illustrates the confidence intervals of the gap predictions with five kernel functions including radial-basis function (RBF), rational quadratic, exponential sine squared, constant, and Matern, respectively. The red dots in the subfigures demonstrate the actual values of gap lengths and the black dots show the predicted gap length from the test data using our surrogate models. Blue range demonstrates the 95 percent confidence interval. By comparing these subfigures in Figure 4 to Figure 3, it can be seen that with a lower number of training points and a smaller number of features, the gap prediction is, as expected, less accurate than using the entire data set. Even though the performance reduced, it is still within an acceptably good range. This is because many of the fifty-eight features from strain gauges are highly correlated. In the future work, we are going to focus on the optimal sensor design problem to make the SHM system more efficient. By comparing these five subfigures, we can realize that their prediction variances are quite different. For example, in subfigure (e), the prediction with kernel function Matern has much larger variances compared to the other four cases. Table III shows the mean values of the standard deviation of these five model predictions.

CONCLUDING REMARKS

In this work, we performed an inverse Kriging analysis on a finite element model by using the strain gauge data for damage (i.e. gap size) identification. We used randomly generated parameters to simulate sample data from ABAQUS. IN this preliminary work, we showed, the surrogate model is formed by choosing hyperparameters of the covariance function that maximizes the likelihood of output, y. Although the prediction is point estimation to the gap sizes,

TABLE III. MEAN OF STANDARD DEVIATION OF TEST DATA

Kernel Functions	Mean of Standard deviation
RBF	0.104
Rational Quadrati	1.995
ExpSineSquared	0.051
Constant	0.017
Matern	2.107

the results shows that the Kriging model can quite accurately predict the gap lengths from the input strain data. We showed that a larger training number induces a better prediction performance of test data. However, if the training number is too large, the computational cost would be relatively high. Moreover, surrogate models with fewer number of features were also analyzed here that demonstrated similar performances to the fifty-eight feature case. In addition, different kernel functions were compared in test accuracy in this work. The result showed that covariance function such as Matern produced surrogate model that had higher variance in predicting gap lengths.

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