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Diagnostic Method for Delamination Monitoring of CFRP Plate using Kriging Interpolation Method

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Abstract. The present paper proposes a new diagnostic tool for the structural health monitoring that employs a Kriging Interpolation. Structural health monitoring is a noticeable technology for aged civil structures. Most of the structural health monitoring systems adopts parametric method based on modeling or non-parametric method such as artificial neural networks or response surfaces. The conventional methods require FEM modeling of structure or a regression model. This modeling needs judgment of human, and it requires much costs. The present method does not require the process of modeling, in order to identify the damage level using the discriminant analysis. This suggest us, this technique is applicable to the health monitoring system, which identifies the damage of the structure, easily. In the present paper, we developed the damage diagnostic methods using Kriging method for identifying delamination from data. Kriging method is a interpolation technique which shown in geostatistic. We applied this method to identifications of delamination crack of CFRP structure. Delamination cracks are invisible and cause decrease of compression strength of laminated composites. Therefore, health-monitoring system is required for CFRP laminates. The present study adopts an electric potential method for health monitoring of graphite/epoxy laminated composites. The electric potential method does not cause strength reduction and can be applied existing structures by low cost. As a result, it was shown that this method is effective for identification of damages.

Introduction

CFRP has high specific tensile strength and stiffness, and are good for the major structures of airplanes and space instruments. The intensity between the layers of CFRP is weak and delamination cracks between layers can be produced by a comparatively slight impact. Such delamination cracks are invisible and cause a decrease of the compression strength of laminated composites. Therefore, a method for diagnosing delamination cracks in laminated composites is required. The present study adopts an electrical potential method for the diagnosis of delaminations in CFRP laminates. Since carbon fiber in a composite material has conductivity, by using an electric potential method, the damage present in a large area of a structure can be diagnosed by conducting electricity through composite structure. The electric potential method does not cause strength reduction and can be applied to existing structures at a low cost. The present study focuses on the electrical potential method of detecting damage in CFRP in the form of delamination cracks.

Recently, many studies have described an electric resistance change method to identify internal damage in CFRP laminates [1,2]. The electric resistance change method does not require expensive instruments. Since the method adopts reinforced carbon fiber itself as sensors for damage detection, this method does not cause a reduction in static strength or fatigue strength, and it is applicable to existing structures. The effectiveness of the electric potential method has been demonstrated in our previous reports [3,4]. In these studies, a delamination crack in a composite beam was identified based on the change in electric potential between electrodes attached to the surface of the composite beam.

The relation between the delamination crack and the change in electric potential is identified by solving an inverse problem. The inverse problem in damage identification is an optimization problems involving estimation error minimization, and is usually solved through the use of such common optimization tools as neural network and genetic algorithm. But in general, trial and error processes are required to derive optimum solutions when using these methods, and these processes demand much calculation and human cost.

We thus propose a method that identifies damage based on statistical analyses for the purpose of constructing a simple method for damage identification. In this method, we use the kriging interpolation as solver for inverse problem. Using the kriging interpolation, damage identification that requires only simple calculation can be performed. In this study, this new method is applied to identify delamination cracks in CFRP beams using the electric potential method. The effectiveness of this method is investigated analytically.

Identification of delamination in a CFRP beam using electric potential method

Analytical model. As mentioned previously, this method for damage diagnosis is applied to the identification of delaminations in a CFRP Beam, and the accuracy of the method is experimentally investigated. FEM analyses are employed for investigations in present study. A detailed description of FEM analysis is provided in our previous studies [3]. The configuration of the specimen used in the present study is shown in Figure 1. The specimen is a CFRP Beam with a thickness of 2mm and a stacking sequence of $[0_2/90_2]$s. In order to measure the change in electric potential caused by a delamination crack, seven electrodes are mounted on the one surface of specimen. The lengths of the electrodes are 10mm. FEM analyses were performed using the commercially available FEM tool named ANSYS. In the present study, four-node-rectangular elements are adopted for analysis; each element is approximately 0.125 mm by 0.125 mm. The specimen model was divided into 28,160 2D elements using the auto-mesh generation system of the ANSYS. A delamination crack is modeled by the release of a nodal point of the element. The electric conductance ratio is obtained from an experimental result regarding a CFRP laminate whose volume fraction is 62% as shown in Table 1.

Procedure for identifying delamination crack. The procedure for identifying a delamination crack using ordinal kriging is as follows: (1) to (3) show the procedure for creating the model variogram(as follow) and (4) to (7) show the procedure for the identification of individual.

(1) The change in electric potential is measured in the various sizes and locations of delamination cracks. These data are referred to as data for learning.
(2) The variogram cloud and the empirical variogram are created based on the data for learning.
(3) Decision of the variogram model, and optimization of the model.
(4) New data is measured for estimation. This data is referred to as individual.
(5) Calculation of the weight matrix.
(6) Estimation of the individual using the ordinal kriging(as follow).

In this study, cross inspections of 474 data are conducted. One data is selected as individual, and the ordinal kriging matrixs are created from other 473 data. This procedure is performed 474 times. In order to simplify the calculations, procedure (2) and (3) are conducted by using all the data.

Kriging Interpolation. Kriging interpolation is one of statistical interpolation method used in geostatistic[5]. The kriging interpolation is used for estimation of parameters which fluctuate depending on space coordinates. The method is mainly used for quality presumption of a mine and a water resources or weather forecast. By the kriging interpolation, the value of arbitrary coordinates is

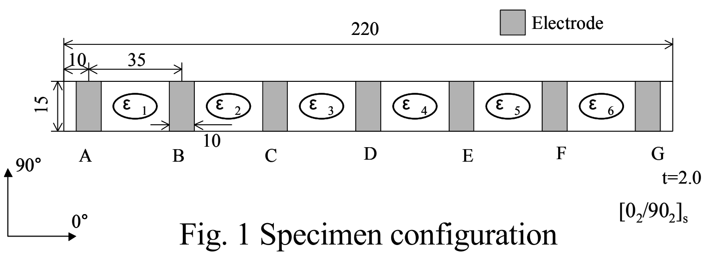

Fig. 1 Specimen configuration

Table.1 Electric conductivity of the specimen

σ_{0°	5535[Ω]
$\sigma_{90^\circ}/\sigma_{0^\circ}$	3.71×10^{-2}
$\sigma_{thickness}/\sigma_{0^\circ}$	3.77×10^{-3}

estimated from all learning data rather than from nearby data. For the estimation, the correlation between the data on coordinates space is analyzed by using a variogram. By this method, it is not required that the learning data should be uniformly distributed on coordinates space.

In the damage estimation by the inverse problems, measurement of the sensors is used as space coordinates. A distribution of the data on coordinates space does not become uniform at most damage estimating problems. Moreover, it becomes estimation on high dimension space. Therefore, in this research, damage diagnosis using the ordinal kriging, which estimates the distribution with the fluctuated average, as the inverse problem method was performed.

Interporation using the ordinal kriging. The kriging is one of the estimation procedure of spatial data between measurement points. The ordinal kriging is one of the kriging which uses the variogram, which shows spacial relation between data, to determine spatial data. When the value in a position s_0 is defined as Z(s_0), Z(s_0) is represented with following formula.

$$Z(s_0)=\sum_{i=1}^{n} w_i Z(s_i) \tag{1}$$

Where n is number of known data, s_i is position of known data, Z(s) is value of the data and w is a weight. As shown in the formula, the value of the arbitrary position is expressed as linear combination of all the known data at the ordinal kriging. The weight w for the ordinal kriging is determined from analysis of a spacial trend which used a variogram. The variogram is a parameter showing the correlation between differential of the data and the distance of the data. The variogram is defined as following formula.

$$2\gamma(h)=\frac{1}{N(h)}\sum_{N(h)}\left(z_i - z_j\right)^2 \tag{2}$$

Where 2γ is the variogram, h is distance, $N(h)$ is number of data which takes distance h and Z is the value. A distribution which shows distance and the variogram about all the known data is called a variogram cloud. For the ordinal kriging, modeling of this variogram cloud is performed to derive the correlation between two data, and estimation of the individual is derived from all data by using the modeled variogram. Procedure for the modeling of the variogram is as follows.

1. Discrimination of the variogram cloud. The discriminated variogram cloud is called an empirical variogram.
2. Selection of the model for fitting of the empirical variogram.
3. Optimization of the parameter of the model. The optimized model is called a model variogram.

In this paper, for fitting of the empirical variogram, following two models are adopted as the model.

A. power model $\gamma(h)=\begin{cases}\theta_0+\theta_1\|h\|^{\theta_2}, & \|h\|>0\\ 0, & \|h\|=0\end{cases}$ B. Gaussian model $\gamma(h)=\begin{cases}\theta_0+\theta_1\left[1-\exp\left(-\{\|h\|/\theta_2\}^2\right)\right] & \|h\|>0\\ 0, & \|h\|=0\end{cases}$ (3)

where θ_0 is a nugget, θ_1 is a sill and θ_2 is a range. The nugget is effect of the noise in the data or variance at lag distances smaller than the sampling interval. The sill describes the variance within the data at distances far enough apart that there is no spatial correlation. The range is the distance at which spatial correlation is no longer evident and the sill has been reached. The model variogram is derived from optimization of these three parameters. By using the model variogram, the weight w of the ordinal kriging is defined as following formula.

$$\begin{pmatrix}\gamma(s_1-s_1) & \cdots & \gamma(s_1-s_n) & 1\\ \vdots & \ddots & \vdots & \vdots\\ \gamma(s_n-s_1) & \cdots & \gamma(s_n-s_n) & 1\\ 1 & \cdots & 1 & 0\end{pmatrix}\begin{pmatrix}w_1\\ \vdots\\ w_n\\ \mu\end{pmatrix}=\begin{pmatrix}\gamma(s_1-s_0)\\ \vdots\\ \gamma(s_n-s_0)\\ 1\end{pmatrix} \tag{4}$$

where s_0 is data for estimation(=individual), s_i-s_j is distance between s_i and s_j and μ is a Lagrangian multiplier. The first matrix of the left side of the formula is fixed by the known data, and the matrix of the right side is derived from distance between the individual and the known data.

As shown in Table 2, each data set consists of the location and size of the delamination crack, and six electric potential change ratios between electrodes ε_i (i=1-6). The electric potential change ratios are normalized by the norm of the measured electric voltage change vector η. The norm of the measured electric voltage change vector and normalized electric resistance changes vector are as following formula. These seven variances, η and v_i (i=1-6), are use as spacial coodinates.

$$\eta = \sqrt{\sum_{i=1}^{6} \varepsilon_i^{\,2}} \qquad \begin{pmatrix} v_1 \\ v_2 \\ \vdots \\ v_6 \end{pmatrix} = \begin{pmatrix} \varepsilon_1/\eta \\ \varepsilon_2/\eta \\ \vdots \\ \varepsilon_6/\eta \end{pmatrix} \tag{5}$$

Result and discussions

Variogram model. Figs. 2 and 3 shows the empirical variogram of location and size diagnosis. The variogram cloud is divided to 100 levels for calculation of the empirical variogram. As shown in the Fig.2 and Fig.3, the variogram of location identification rises exponentialy with increase of the distance, and the variogram of size identification is converged to a constant value. Since the empirical variograms shows such tendency, power model and gaussian model are used for the variogram model. A solid line of the figures shows the optimized variogram model. The fitting model of the location variogram and the size variogram is as follows. Where h shows distance and γ shows variogram.

$$\text{location:} \quad \gamma(h) = 2.43 * 10^3 \|h\|^{1.41}, \qquad \text{size:} \quad \gamma(h) = 0.0512 + 2.85\left[1 - \exp\left(-\left\{\|h\|/5.76\right\}^2\right)\right] \tag{6}$$

Identification of location of delamination crack. The results of the delamination location estimations obtained are shown in Fig.4. The abscissa is a actual location and the ordinate is the estimated location. The symbols plotted on the diagonal line means the estimation are exact. As shown in the figure, a large error has occurred in the data of y= 115 and -115.

At these areas, change of the electric resistance was quite small because of the middle of the electrodes. This small change of the electric resistance causes large error. However, the error of other portions is less than 3mm, and estimation by the kriging shows quite good accuracy.

Identification of the size of the delamination crack. The results of the delamination size estimations obtained are shown in Fig.5. Since the size of the delamination crack is divided to 5 levels (5, 10, 20, 30 and 40 mm), the result shows such a discreat distribution. As shown in the figure, distribution of the estimation is not overlapping and most data belongs to the actual level. Table 2 shows diagnostic accuracy. As shown in the table, since the sections are approaching about 5 or 10mm, diagnostic accuracy of the delamination cracks of 5 or 10mm is poor than the others. However as shown in the figure.6, since an error band of the estimation is less than 3.5m, the size is estimated to the actual level or the neighbor levels. It has sufficient accuracy for practical diagnosis. Thus, generalization capability of the kriging interpolation is high and sufficient for the damage identifying method.

Table 2 Data for estimation

Test No.	Location	Size	Electric potencial change ratio					
	[mm]	[mm]	ε_1 (AB)	ε_2 (BC)	ε_3 (CD)	ε_4 (DE)	ε_5 (EF)	ε_6 (FG)
1	31	20	0.00E+00	0.00E+00	3.96E-02	4.70E+00	5.03E+00	1.09E-02
2	-16	30	5.47E-03	1.62E+00	1.95E+00	2.86E+00	0.00E+00	0.00E+00
3	-37	40	2.68E-01	1.19E+01	1.26E+01	1.25E-01	0.00E+00	0.00E+00
⋮	⋮	⋮					⋮	
474	1	40	0.00E+00	1.47E-01	1.25E+01	1.21E+01	2.26E-01	0.00E+00

Conclusions

The present paper describes a new method using simple calculation for the identification of delamination cracks in CFRP beams through the application of the kriging interpolation. The main conclusions are as follows:

1. The kriging interpolation shows high accuracy in identifying delamination in CFRP beams using the electric resistance method.
2. Damage diagnosis using the kriging interpolation shows a high generalization capability. Therefore the method is suitable for the damage diagnosis method.

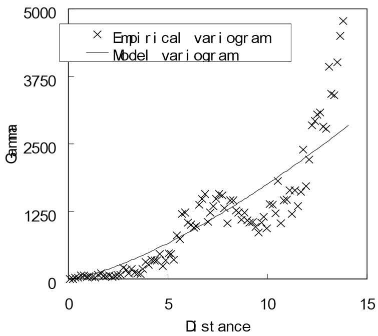

Fig. 2. Empirical variogram(location)

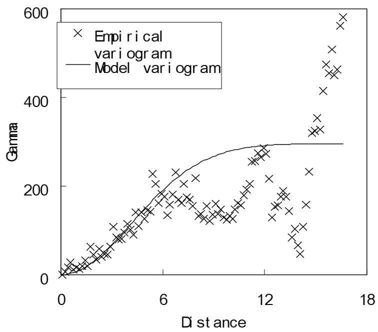

Fig. 3. Empirical variogram(size)

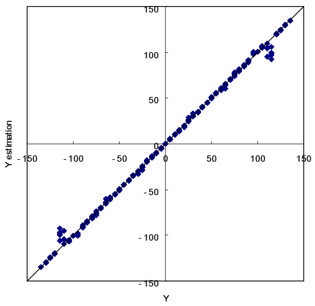

Fig. 4. Result of location identification

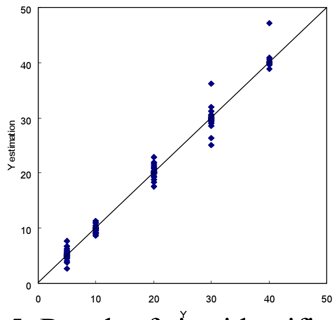

Fig. 5. Result of size identification

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