ULTRASONIC SENSOR PLACEMENT OPTIMIZATION IN STRUCTURAL HEALTH MONITORING USING EVOLUTIONARY STRATEGY

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ABSTRACT. In structural health monitoring (SHM), sensor network scale and sensor distribution decisions are critical since sensor network performance and system cost are greatly affected. A quantitative sensor placement optimization method with covariance matrix adaptation evolutionary strategy (CMAES) is presented in this paper. A damage detection probability model is developed for ultrasonic guided wave sensor networks. Two sample problems are presented in this paper. One is for structure with irregular damage distribution probability, and the other is for an E2 aircraft wing section. The reliability of this genetic and evolutionary optimization method is proved in this study. Sensor network configurations with minimum missed-detection probability are obtained from the results of evolutionary optimization. The tradeoff relationship between optimized sensor network performance and the number of sensors is also presented in this paper.

Keywords: sensor, optimization, SHM, evolutionary strategy, ultrasonics
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INTRODUCTION

Structural health monitoring (SHM) is the process of implementing a damage detection strategy for aerospace, civil, and mechanical infrastructures. Most of the structural components are natural waveguides. This provides the ultrasonic guided waves with tremendous opportunity to interrogate the health condition of the structures through wave excitation, propagation, and detection. Ultrasonic guided wave based methods have been recognized as a major part of SHM research.

In the area of guided wave based SHM, much effort has been directed in the areas of wave propagation mechanics and sensor design [1]. However, only few works have been reported on the sensor network level design and optimization. [2,3]. The work presented in this paper aims at developing a quantitative sensor placement optimization methodology for ultrasonic sensor network performance enhancement and cost reduction. A damage detection probability model is brought out, in which radial basis functions are used to represent the effective coverage of an individual sensor.

Genetic and evolutionary algorithms (GEA) are population based optimization algorithms, in which the exploration of searching space is guided by selection and genetic operators such as cross over and mutation [4]. Within a short time since its emerging, GEA

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has achieved exponentially increasing applications in many research areas. Covariance matrix adaptation evolutionary strategy (CMAES) developed by Nickolaus Hansen is particularly capable of solving problems with highly nonlinear, concave, and rugged search landscapes [5]. Sensor network configurations are optimized toward minimum miss-detection probability with CMAES in this paper. CMAES reliability assessment are performed with random seed analysis. Two sample problems are presented in this paper. One is for a structure with irregular damage distribution probability, and the other is for an E2 aircraft wing section. The relation showing the trade off between optimized performance and the number of sensors is obtained.

THEORIES

A Probabilistic Damage Detection Model

Ultrasonic wave propagation characteristics are governed by the theories of mechanics, material properties, and structural boundary conditions. In an isotropic structure, the wave propagation from a omni directional sensor is axi-symmetric. When material attenuation is negligible, ultrasonic signal strength is approximately proportional to the reciprocal of the distance between the sensor and the damage event. Based on this assumption, a statistical effective region of a sensor can be expressed with Equation 1. In Equation 1, a confident monitoring region is defined by a circle with radius R_1. The damage detection probability decreases with distance until it reaches R_2. When the distance is larger than R_2, the signal is no longer resolvable from the system noise and the sensor loses its effectiveness totally in this region.

$$P(x,y,x_0,y_0)=\begin{cases}1 & when \quad R<R_1\\ \dfrac{R_1}{R} & when\, R_1<R<R_2\\ 0 & when \quad R>R_2\end{cases}. \tag{1}$$

Here, $R=\sqrt{(x-x_0)^2+(y-y_0)^2}$,

(x,y) is the position of the damage event, and (x_0,y_0) is the position of the sensor.

The entire effectiveness of a sensor network is the joint effect of all of the sensors. Based on the theory of probability, the sensor network sensitivity at a certain point is the union probability of all the sensors.

$$P(x,y)=\bigcup_{i=1}^{SN}(P(x,y,x_i,y_i)). \tag{2}$$

Sensor network performance can be evaluated by its damage detection probability for the entire structure. Case history study information is used for guidance in sensor placement optimization. When the normalized damage distribution on the structure is $P_d(x,y)$, the damage detection probability for the entire structure is defined in Equation (3).

$$DDP=\iint\limits_{Stucture\ region} P(x,y)P_d(x,y)dxdy. \tag{3}$$

Here, the normalization of $P_d(x,y)$ is expressed as

$$\iint_{Structure\ region} P_d(x,y)dxdy = 1 \quad . \tag{4}$$

Enhancing the performance of the sensor network is equivalent to minimizing the miss-detection probability (MDP).

$$MDP = 1 - DDP\,. \tag{5}$$

The minimization of MDP is essentially to place the sensors at the structural hotspots defined by case history damage distribution.

CMA Evolutionary Strategy

CMA evolutionary strategy (CMAES) is a heuristic optimization algorithm. The initial population is generated by sampling a normal distribution with user specified mean value and standard deviation of each decision variable. Offspring generation, selection and recombination, covariance matrix adaptation, and step size control are four key operators in the process of evolution. A searching iteration stops when user specified convergence or any other stop criterion is met.

A new population is sampled from a normal distribution specified by

$$x_k^{(g+1)} \sim N(m^{(g)}, (\sigma^{(g)})^2 \mathbf{C}^{(g)}) \tag{6}$$

for $k = 1,2,\ldots,\lambda$

Here, λ is the population size; $x_k^{(g+1)}$ is the k^{th} sampled individual of generation (g+1).

$N(m^{(g)}, (\sigma^{(g)})^2 \mathbf{C}^{(g)})$ is a multivariate normal distribution in generation (g). $m^{(g)} \in R^n$ is the mean value of decision variables in generation (g); $\sigma^{(g)} \in R_+$ is the "overall" standard deviation, which is also termed step size; $\mathbf{C}^{(g)} \in R^{n\times n}$ is the covariance matrix. *n* refers to the number of decision variables.

SAMPLE SENSOR NETWORK DESIGN PROBLEMS

A Sample Problem of Irregular Damage Distribution

In this sample problem, normalized sensor and structure scale is used. The monitored region is 100x100. The sensor performance parameter R_1 and R_2 are 3 and 40 respectively.

The case history damage distribution is shown in Figure 1. In this sample structure, the damages are most likely to happen in two elliptical areas at two sides and at the center of the plate. The optimization problem is to minimize the MDP function in Equation (7) when the number of sensors is given. When the sensor number is N, there are 2N real decision variables including the x and y coordinate positions of the sensors. No other geometric constraints are used except for boundaries of the monitoring region. The evolutionary search stops when the maximum standard deviation of the decision variables is smaller than 0.25.

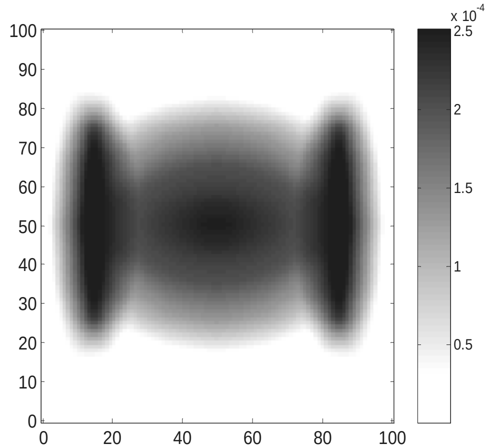

FIGURE 1. Damage probability distribution.

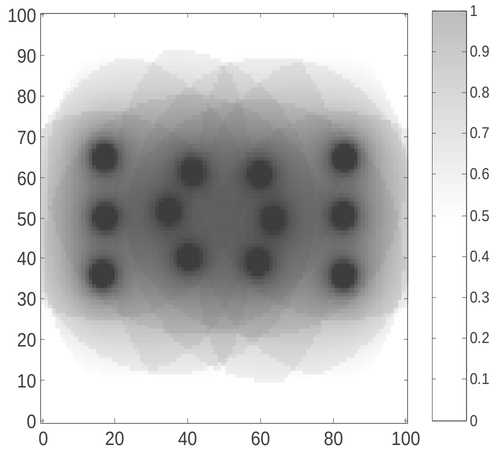

FIGURE 2. Sensor detect ability distribution of the best sensor configuration.

The sensor network sensitivity distribution of the optimized configuration is shown in Figure 2. This figure shows that the sensor placement result from the CMAES optimization generally fits the structure hotspot. The MDP of the optimized sensor distribution is 11% less than the original random distribution.

Forty different random number seed runs are used to evaluate the reliability of this CMA evolutionary strategy. The mean value and standard deviation of the best MDP solution and its corresponding function evaluations are listed in Table 1. Very small standard deviations of the optimized MDP value is observed from the 40 runs. In addition, the standard deviation of the number of function evaluation toward convergence is also comparably small to the average number of function evaluation. Therefore, the CMAES with default parameter setting has a good performance in terms of its reliability.

TABLE 1. Statistic analysis of algorithm reliability.

40 random number seeds	Optimized solution	
	MDP (%)	Function evaluation
Mean	27.25	2536
Standard deviation	0.0106	381

The relation between optimized miss detection probability, sensor number and sensor parameters are shown in Figure 3. Two types of sensors are studied. For sensor type 1, R_1 equals to 3. For type 2, R_1 equals to 5. This figure shows that when the optimized sensor distribution is obtained, individual sensor performance, and the sensor number affects the overall performance of the sensor network. The quantitative relation between the sensor number and sensor network performance is very important for the overall safety and cost of the monitoring system. For a given safety requirement, the minimum number of sensors can be obtained from the tradeoff curves.

A Sample Structure of an Aircraft Wing Section

A more realistic testing sample of an E2 aircraft wing section is considered in this section. The photo of the aircraft wing section is in Figure 4. Case history study shows that crack initiation has the largest probability around rivet holes. A high-resolution damage distribution grid is used to resolve the damages in sub-millimeter scale. In addition, the sensors are not preferred to be placed on the regions of stiffening ribs for the monitoring of wing skin. In optimization language, these are the infeasible spaces for the decision variables. When the sensor performance parameters R_1 and R_2 are 20mm and 80mm respectively, a sample sensor distribution result for the case of an 8 sensor network is shown in Figure 5. The black regions in Figure 5 represent the stiffening ribs. The gray circles represent the optimized location of the sensors.

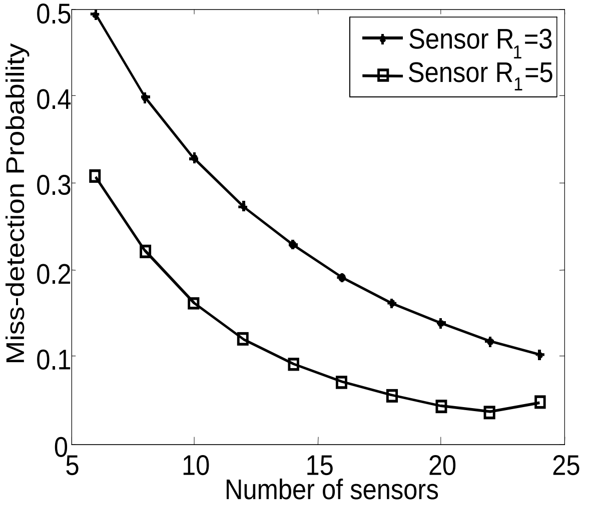

FIGURE 3. Relation between MDP, sensor number and sensor performance.
Sensor Type 1: R_1=3; Sensor Type 2: R_1=5.

FIGURE 4. An E2 aircraft wing section.

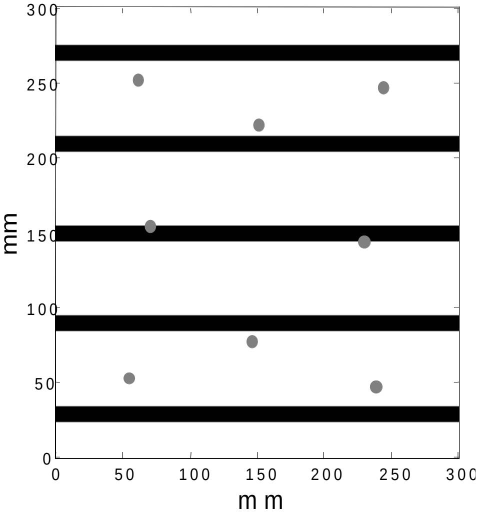

FIGURE 5. Sample optimized sensor distribution of an 8 sensor network on the wing section.

CONCLUSIONS AND DISCUSSIONS

CMA-ES were used to solve the problem of sensor number and sensor distribution decisions in structural health monitoring. An optimized sensor configuration can be obtained for a structure being monitored. Two sample problems are discussed in this presentation. In the first sample problem of an irregular damage distribution, the results from CMAES improved 11% of MDP from a random placement configuration. The second sample problem is an aircraft wing skin structure, in which high resolution damage detection sensors are placed to their optimized locations. The results from the statistic damage detection model provided a quantitative relation of the tradeoff between overall sensor network performance, sensor number, and the performance of each individual sensor. This technology is very valuable for the implementation of structural health monitoring sensor networks onto real structures.

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