IMPROVING CONTROL EFFICIENCY BY USING MORE DISTRIBUTED SENSORS IN SMART STRUCTURE CONTROL

Yi-Lun Chu, Tzu-Kang Lin, Kuo-Chun Chang
National Center for Research on Earthquake Engineering, Taipei, Taiwan
ylchu@ncree.org.tw

Abstract

Nowadays, Fiber Bragg Grating sensors(FBG) have been proven to be immune from electronic and magnetic field. By the support of FBG sensors, the advantage and feasibility of applying many distributed sensors in active control becomes an interesting subject. This paper presents the advantage of using many FBG sensors as feedback in smart structure control. To implement the concept of the smart structure, genetic algorithms (GAs) is embedded in this study to search for the optimal control gain for the control force. In order to evaluate the performances, three sets of feedback with different sensors were used. For the first set(case 1G), the 8th-floor strain sensor was selected as feedback. For the second set(case 3G), the 8th-floor, 7th-floor and 6th-floor strain sensors were chosen, and for the last set(case 8G), all strain sensors in each floor were used as feedback. The structural responses of each set under earthquake excitations were simulated and compared. According to the analysis results, increasing the amount of distributed sensors used as feedback can improve the control efficiency.

INTRODUCTION

Civil structures, especially for high-rise buildings, are usually large in scale. Thus the control of civil structures requires large energy and efficient control design methodology. The feedback selection to determine the control action is usually assumed that the amount of measured feedback is limited. In recent years, the development of technology progresses prosperously. A variety of smart materials have been proposed in many literatures(Soong et al.2002 and Culshaw et al. 1996)) and also widely used in the application of civil structures. One of the most popular is Fiber Bragg Grating sensors.(Lin 2002) With the support of FBG sensors measuring the structure responses, applying large amount of distributed sensors in structures is becoming feasible. Many feedback control methodologies of active control have been studied for the optimization of control performance.(Kim et al. 1999) A control efficiency evaluation of a high-rise building under wind-excitation has been carried out by using genetic algorithms.(Kim et al. 2001) Although these studies have provided much valuable information about the control design methodology, the amount of the feedback signals is still limited. The purpose of this study is to increase the control efficiency by adding more sensor feedback into the controller optimization process with the help of genetic algorithms. The evaluation concept and procedure is shown in Fig.1.

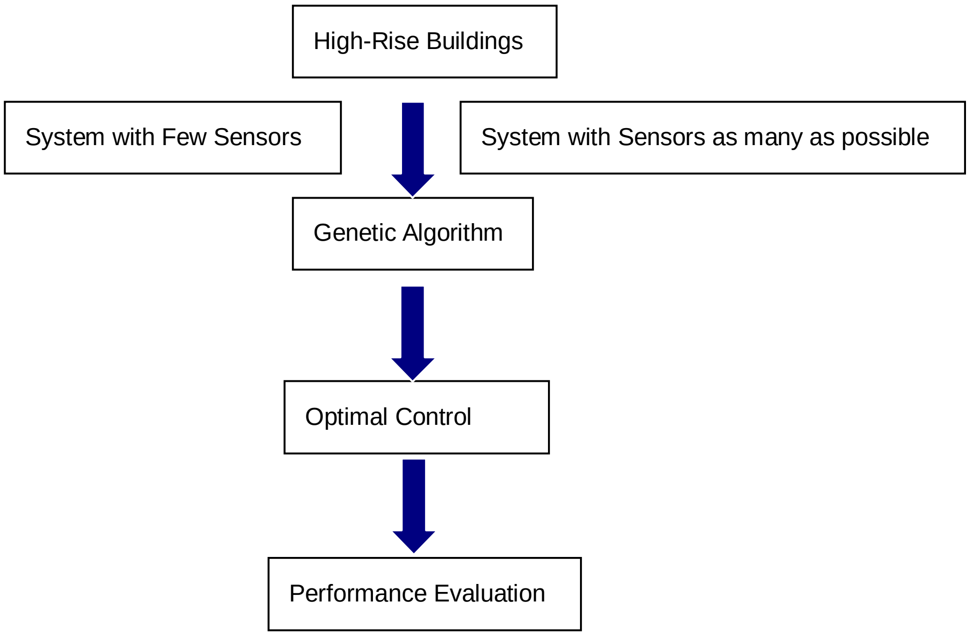

Fig.1 Flow chart of the evaluation of the advantage of distributed sensors

GENETIC ALGORITHMS

Genetic algorithms, which are based on the mechanism of evolution and biological systems, is often used for optimization in many fields. The variables are coded into genetic strings known as chromosomes and represented by bit strings. Each string contains several sub-strings, called genes, which have different combinations to fit the optimization of the problem. The optimization was achieved through the fitness function that characteristics the performance of each individual string. There are three operators in genetic algorithms: selection, cross-over and mutation. Selection is the process of choosing the fittest parameters from current population to yield better generations. Cross-over is to exchange information between pairs to have new offspring strings. Mutation is a random process which causes the individual string to be changed according to the probabilistic rule. Mutation is generally considered to ensure the diversity of the population. This will inhabit the possibility of converging to the local optimum, rather than global optimum.

PROBLEM DESCRIPTION

The model considered in this study is an eight-storey structure commonly referred in active control research.(Yang et al. 1987) The structure property for each story unit is the same for illustrative purposes. The floor mass is 345.6 tons; stiffness is 340,400 kN/m and the internal damping force is 2,937 tons/sec. Eight FBG strain sensors, in total, were distributed in this model at the lower-end of the column for each floor. To evaluate the performance of the distributed sensors selected as control feedback, three sets of selection combination were proposed. The first set, case 1G, only the 8th-floor strain sensor was selected as feedback. In the second set, case 3G, the 8th-floor, 7th-floor and 6th-floor strain sensors were chosen, and for the last set (case 8G), all the strain sensors in each floor are used as feedback. The actuator was placed between the base and the first floor for the best control efficiency.(Yang et. al 1983) Fig 2. shows the sketch of the model. The locations of distributed FBG sensors and actuator are also shown in the figure.

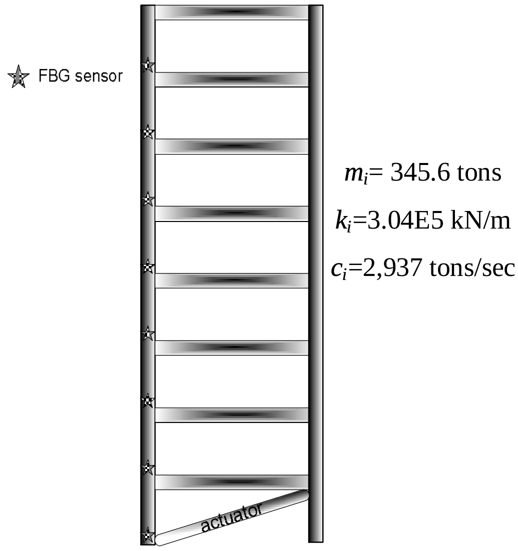

Fig. 2 Sketch of the model

CONTROL DESIGN METHODOLOGY

The methodology of the optimal controller design was described in this section. In this study, strains and actuator force (control signal) are used as feedback to obtain the optimal control gain. The controller design uses previous time histories of strains $y(t)$ and control force $u(t)$ as feedback in the process of control gain optimization. For this study, twelve previous strain histories and three previous control signals are selected as feedback to calculate the control gain at time *t*., The feedback vector in case 1G for example is in the following form:

$$Y_{1G}(t) = \left[y_1(t-t)\, y_1(t-2t)\, y_1(t-3t) \ldots y_1(t-12t)\, u_{1G}(t-t)\, u_{1G}(t-2t)\, u_{1G}(t-3t) \right]_{1\times 15}$$

The control force $u(t)$ was calculated by the multiplication of control gain matrix G and feedback vector $Y(t)$, which are shown in the following equations:

$$u_{1G}(t) = G_1 \times Y_{1G}(t)\,;\, u_{3G}(t) = G_3 \times Y_{3G}(t)\,;\, u_{8G}(t) = G_8 \times Y_{8G}(t)$$

The control gain matrix G is optimized by using genetic algorithms. In the optimization process, the mutation rate is set to 0.003, the cross-over rate is set to 0.8 and the evolution numbers up to 300 generations. The actuator control force $u(t)$ is constraint to max $|u(t)| \leq 10000$ kN.

ANALYTICAL RESULTS AND COMPARISON

Numerical simulations of the three cases proposed in this study have been carried out. The earthquake history used in simulation was the scaled 0.3g El Centro earthquake. Fig.3 shows the fitness function reduction process through the evolution for each case. It can be seen that the value of the fitness function decreases as the generation increases, which proved the feasibility of applying GAs into the optimization process. The value of the fitness function also became much smaller as using more sensors as feedback. In other words, the best fitness function value of case 8G is smaller than those of the other two cases.

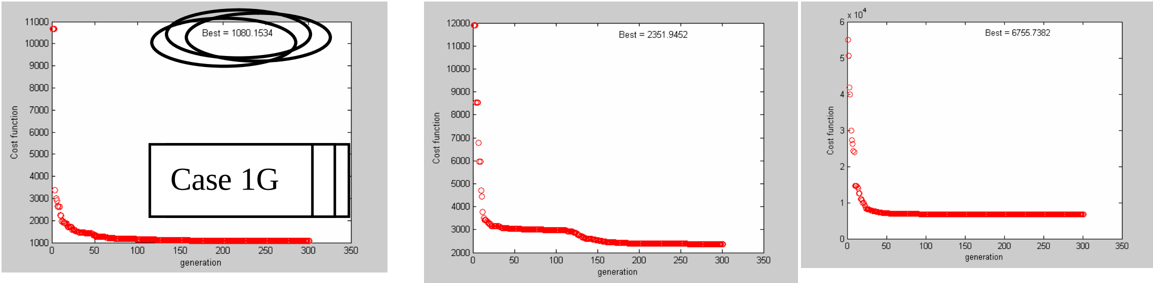

Fig.3 Cost of the fitness function for each generation

The overall performance of the control design was evaluated based on the peak and root-mean-squared (RMS) response of the structure. From Table 1, which listed the numerical analysis results of the floor peak displacement, it can be observed that the peak lateral roof displacement reduction percentage of the model with actuator under scaled the 0.3g El Centro for case 1G, 3G and 8G were 33%, 46% and 53%, respectively. The peak lateral acceleration responses were listed in Table2. The RMS values of the displacement and acceleration of each floor were listed in Table 3 and Table 4.

The optimized control forces histories of the three cases were plotted in Fig. 4. The time histories of the roof displacement and the roof acceleration response values for the three cases were plotted in Fig. 5 and Fig. 6, respectively. As expected, case 8G can improve the performance by about 60% as compared to case 1G, which means the more feedback used in searching for the optimal control gain, the better performance can be achieved.

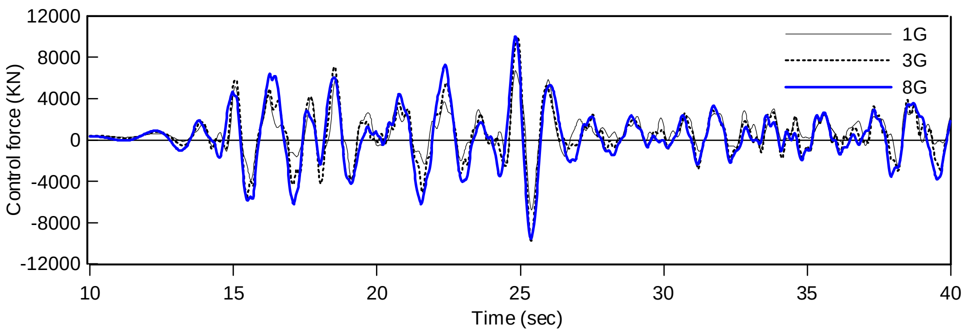

Fig.4 Control force histories

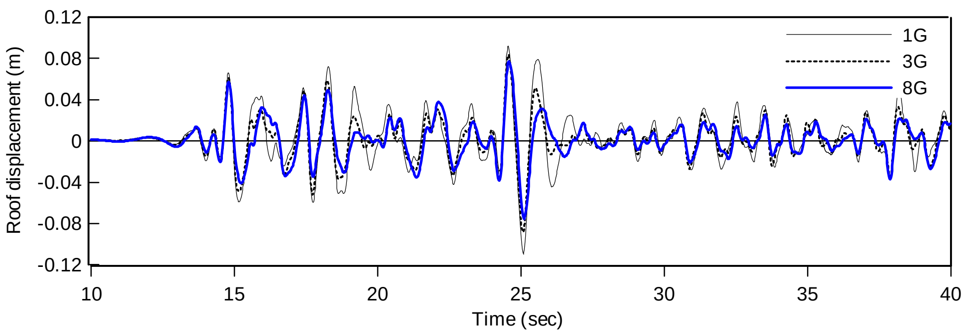

Fig.5 Controlled displacement responses

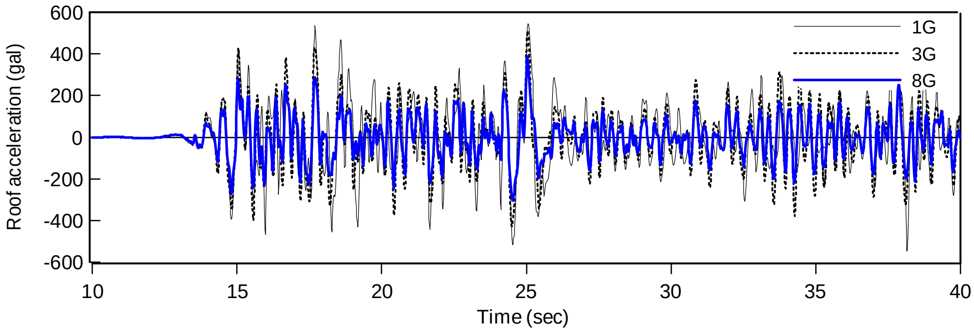

Fig.6 Controlled acceleration responses

CONCLUSION

The advantage of using distributed sensors in smart structure control has been evaluated by using GAs and FBG sensors. The controller performance is evaluated by considering as many sensors as possible and the structural control efficiency improves as the amount of distributed sensors selected as control feedback increases. The result gas determined that it is feasible to apply many sensors into the active control algorithm to achieve better performance.

REFERENCES

Culshaw, B., Michie, C., Gardiner, P. and Mcgown, A.(1996) "Smart structures and applications in civil engineering." *Proceedings of the IEEE*, vol. 84, No.1, January

Kim, Y.T. and Ghaboussi J.(1999) "A new method reduced order feedback control using genetic algorithms." *Earthquake Engng. Struct. Dyn.* 28,193-212

Kim, Y.T. and Ghaboussi J.(2001) "Direct use of design criteria in genetic algorithm-based controller optimization." *Earthquake Engng. Struct. Dyn.* 30,1261-1278

Lin, T.K. (2002). "Neural network control of structure with FNG optical sensors." *Ph.D. dissertation*, National Taiwan University, 2002.

Soong, T.T. et. al(2002). "Recent development in structural control." *Engineering structures*, vol.3, special issue, March 2002.

Yang, J. N. and Samali B.(1983) "Control of tall buildings in along-wind motion." *Journal of Structural Engineering*, 109,50-68

Yang, J. N., Akbarpour, A. and Ghaemmaghami, P.(1987) "New optimal control algorithms for structural control." *Journal of Engineering Mechanics.* 1vol. 13, no. 9, 1369-1386

Table 1. Peak lateral displacement and the reduction percentage of the model

Displacement(cm) Reduction Percentage(%)								
Case	8F		7F		6F		5F	
un	16.4		15.7		14.5		12.8	
1G	11.0	33.0%	10.4	33.8%	9.4	35.4%	7.9	37.9%
3G	8.8	45.9%	8.3	47.0%	7.4	48.9%	6.2	51.2%
8G	7.7	53.0%	7.4	52.9%	6.9	52.5%	6.1	52.1%
Case	4F		3F		2F		1F	
un	10.7		8.3		5.7		2.9	
1G	6.3	41.0%	4.6	44.3%	3.2	45.0%	2.3	21.0%
3G	5.0	53.3%	3.8	54.6%	3.2	44.5%	2.6	12.7%
8G	5.2	51.0%	4.5	46.2%	3.9	32.8%	3.1	-7.5%

Table 2. Peak lateral acceleration and the reduction percentage of the model

acceleration(gal) Reduction Percentage(%)								
Case	8F		7F		6F		5F	
un	749.3		654.6		559.3		486.3	
1G	546.6	27.1%	488.3	25.4%	441.1	21.1%	406.6	16.4%
3G	511.5	31.7%	441.1	32.6%	346.1	38.1%	373.0	23.3%
8G	388.2	48.2%	323.8	50.5%	245.0	56.2%	258.8	46.8%
Case	4F		3F		2F		1F	
un	440.7		489.8		513.9		375.5	
1G	385.2	12.6%	406.3	17.0%	432.8	15.8%	419.9	-11.8%
3G	338.3	23.2%	336.0	31.4%	318.7	38.0%	314.1	16.4%
8G	225.0	48.9%	247.6	49.4%	245.3	52.3%	268.6	28.5%

Table 3. RMS lateral displacement and the reduction percentage of the model

Displacement(cm) Reduction Percentage(%)								
Case	8F		7F		6F		5F	
un	4.7		4.5		4.2		3.7	
1G	2.2	53.1%	2.1	53.5%	1.9	54.3%	1.7	55.2%
3G	1.7	63.6%	1.6	64.1%	1.5	64.9%	1.3	65.6%
8G	1.6	66.4%	1.5	66.3%	1.4	66.1%	1.3	65.5%
Case	4F		3F		2F		1F	
un	3.2		2.5		1.7		0.9	
1G	1.4	56.0%	1.1	56.4%	0.8	55.4%	0.5	43.8%
3G	1.1	66.0%	0.9	65.8%	0.6	63.1%	0.5	41.3%
8G	1.1	64.0%	1.0	60.7%	0.8	52.2%	0.7	19.5%

Table 4. RMS lateral acceleration and the reduction percentage of the model

acceleration(gal) Reduction Percentage(%)								
Case	8F		7F		6F		5F	
un	193.1		168.5		148.0		139.5	
1G	133.6	30.8%	106.2	37.0%	90.3	39.0%	86.6	38.0%
3G	123.1	36.3%	93.7	44.4%	71.6	51.6%	76.4	45.3%
8G	83.2	56.9%	65.2	61.3%	54.2	63.4%	55.9	59.9%
Case	4F		3F		2F		1F	
un	139.6		137.1		122.6		88.9	
1G	88.1	36.9%	97.9	28.6%	106.8	12.9%	104.4	-17.4%
3G	98.2	29.7%	98.1	28.5%	85.7	30.1%	85.8	3.5%
8G	65.1	53.4%	64.1	53.2%	58.6	52.2%	69.6	21.7%