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EXPERIMENTAL VERIFICATION OF A BIO-INSPIRED STRUCTURAL HEALTH MONITORING SYSTEM

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ABSTRACT

A structural health monitoring system based on Bayesian damage classification and DNA expression data is studied in this paper. Transplanted from the DNA array concept in molecular biology, the proposed structural health monitoring system is constructed by utilizing a double-tier AR-ARX regression process to extract the expression array from the structural time history recorded during external excitations. The AR-ARX array is symbolized as the various genes of the structure in the viewpoint of molecular biology to reflect the possible damage condition existing in the structure. A scale-down six-story steel building located at the shaking table of the National Center for Research on Earthquake Engineering was used as the benchmark structure, and the structural response with different damage levels and locations under ambient vibration was collected to support the database for structural health monitoring. To improve the feasibility of the proposed structural health monitoring system in practical application, the system is upgraded again using the likelihood selection method. The AR-ARX array representing the DNA array of the health condition of the structure is first evaluated and ranked. Totally 30 groups of expression array are regenerated from the combination of six damage conditions.. To keep the coefficient number unchanged, the best four coefficients among every expression array are selected to form the optimized structural health monitoring system, and the sequence of the array coefficients is assembled based on the likelihood score calculated for each coefficient. Test results from ambient showed that comparing to the previous damage classification system, the detection accuracy of structural damage can be enhanced by the optimized AR-ARX array perfectly. The feasibility of transplanting the DNA array concept from molecular biology into the field of structural health monitoring has been demonstrated by the proposed SHM system.

Introduction

Structural health monitoring (SHM), a brand new multidisciplinary field, gradually

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emerges in various branches of engineering over the last fifteen years. Generally, SHM is defined as the implementing of damage detection and characterization strategy for engineering structures. For the regularity and mass production characteristics of the monitoring objectives, some developed SHM technologies have been successfully applied to aircrafts, vessels, and vehicles in both aeronautics and mechanical engineering. For civil engineering, the goal of SHM is to provide rapid condition screening and reliable information regarding the integrity of the structure in near real time after extreme events, such as earthquakes or blast loading. To reach this target, researchers have been focusing on developing some specific techniques and customized systems.

Recently, how to apply the concept of pattern recognition technique to the field of SHM has been widely discussed. By using pattern recognition technique, the SHM system should be able to classify the measured data based on a priori knowledge or statistical information extracted from the collected patterns. As this concept is increasingly accepted by worldwide researchers, SHM systems based on pattern recognition technique are established and verified. For example, a novel time series analysis integrating pattern recognition is first proposed by Sohn et al. [Sohn and Farrar 2001]. The statistical process control (SPC) technique is then combined to improve the performance of the system [Sohn et al. 2000]. To prove the practical feasibility of pattern recognition based system, experimental data measured from full-scale civil structures are used. It is found that although damage can be consistently detected, however, problems still exist when localizing or quantifying are required [Cheung et al. 2008].

Bioinformatics, the application of information technology to the field of molecular biology, rapidly attracts the vision from researchers of all fields after it was coined in 1979. The research conducted by Dominggos and Pazzani demonstrates that attributes can be dependent in a simple Bayesian classifier (SBC) and makes the application of SBC in bioinformatics possible [Domingos and Pazzani 1996]. Later, the concept of gene expression monitoring was proposed and implemented by T. R. Golub in 1999 [Golub et al. 1999]. The new method offers a new vision for classifying cancer cells from normal ones and ignited a series of researches on detecting diseases from gene expression array. Following the study, a new research using Naïve Bayes (NB) algorithm to identify the DNA array of cells was proposed [Keller et al. 2000]. Different cancer cases were classified by comparing the DNA patterns of cells with the NB algorithm. According to the research result, the possible disease can be reliably diagnosed by the new proposed system. The subsequent research from Slonim et al. once again demonstrated the feasibility of combining the NB algorithm and the DNA array data for multi-class cancer diagnosis [Slonim et al. 2000].

Inspired by the above-mentioned researches, a new SHM system is proposed in this paper. The structural damage characteristic was first extracted by an AR-ARX model which is composed of a double-tier auto-regressive (AR) and auto-regressive with exogenous inputs (ARX) prediction model. By evaluating the AR-ARX array calculated from the measured structural response with the database created from different structural damage conditions under the support of NB algorithm, the possible damage location and level can be rapidly detected. As verified in the study, approximately 75-80% accuracy of the system was demonstrated. An optimization process using likelihood selection method is studied in this paper to improve the SHM system developed.

Experiment Verification

The proposed SHM system is composed of three parts: the AR-ARX expression array database which is converted from the time history of structural response under specific damage conditions, the Naïve Bayes method which has been demonstrated to have superior performance in array classification, and the likelihood selection process to optimize the SHM system. To verify the feasibility of the proposed SHM system in practical structure, a series of experiment was conducted on the scale-down six-story specimen at National Center for Research on Earthquake Engineering (NCREE).

Ambient Vibration Test

Different from monitoring the structural response during strong earthquakes, which is commonly seen in some existing SHM systems, the proposed system tries to use signals measured from ambient vibration in the daily life to enhance its practicability. The structure damages were classified into four major groups with 13 different cases and were simulated by loosening four of the 16 bolts in each floor (1/4 of the beam-column connection). By collecting the experiment database at night, the unwanted noise due to the machine operation or human activity from the laboratory can be carefully avoided and suppressed to improve the reliability of the structural feature arrays. A list of the thirteen damage conditions is listed in Table 1.

As shown in Figure 1, six high-sensitivity velocity meters were deployed on the specimen to measure the micro vibration of each floor. The sampling rate was set to 200 Hz, and 90 cases with each of 20 seconds under every damage condition were recorded while the 13 damage cases were achieved by switching the location of the loosened fasteners. The SHM database was then established by transforming the time histories into the above mentioned AR-ARX models as the DNA array of the structure. The three fundamental parameters (p, a, and b) of the basic ARA-RX model described is designed to be 12-8-4 after an optimization process. Meanwhile, the advantage of utilizing array expression data for SHM is evaluated by using five different array orders of 60-40-20, 72-48-34, 84-56-28, and 96-64-32 under the basis of the 12-8-4 form. As indicated itself, the 60-40-20 AR-ARX array uses 120 coefficients to monitor the health condition of the structure, and the 96-64-32 AR-ARX array uses 192 coefficients accordingly. To execute the independent testing of the SHM system, 80 patterns in each damage case were used to create the SHM array database, and the rest 10 patterns were used to verify the performance of the system. The results of all 13 cases by sensor V6 is shown in Figure 2. The 13 damage cases are indicated in the longitudinal axis as UN, S1, S2, S3, S4, S5, S6, M12, M34, M56, S123, S234, and S456, and the detected damage condition is reflected in the latitudinal bar. The AR-ARX order is increased from 60-40-20 from the top subplot to the final 96-64-32 in the bottom subplot. All the 10 testing patterns are expressed by the individual bar among every damage case.

According to the results shown in the figures, the performance of the SHM system can be enhanced by increasing the order of the AR-ARX array data. For the cases of 60-40-20 and 72-48-24, serious fluctuation is observed among all testing cases. It is estimated that structural damage characteristics may not be reflected by using only few coefficients. With considering high-order array expression data, the minute damage existing in the structure can successfully detected. For the 96-64-32 AR-ARX system, the accuracy can be expected to approximately 85 to 90 %. Although the feasibility of the proposed SHM system with high-order AR-ARX has been demonstrated by the previous examination, however, any SHM system without 100 % precision could still be classified as a failed system. For that reason, the developed SHM system is upgraded again by using the likelihood selection method in the next section.

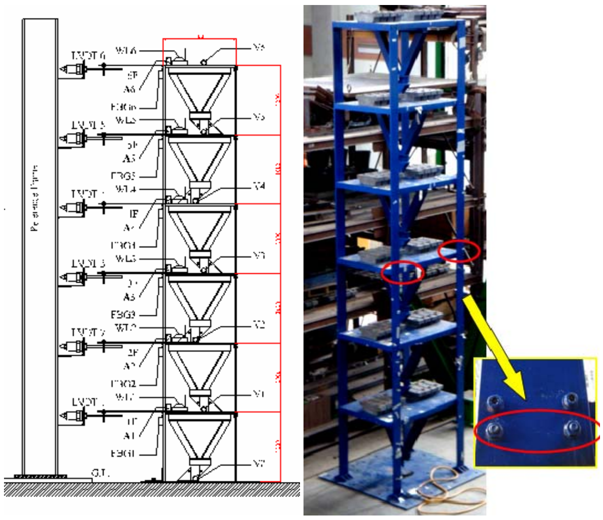
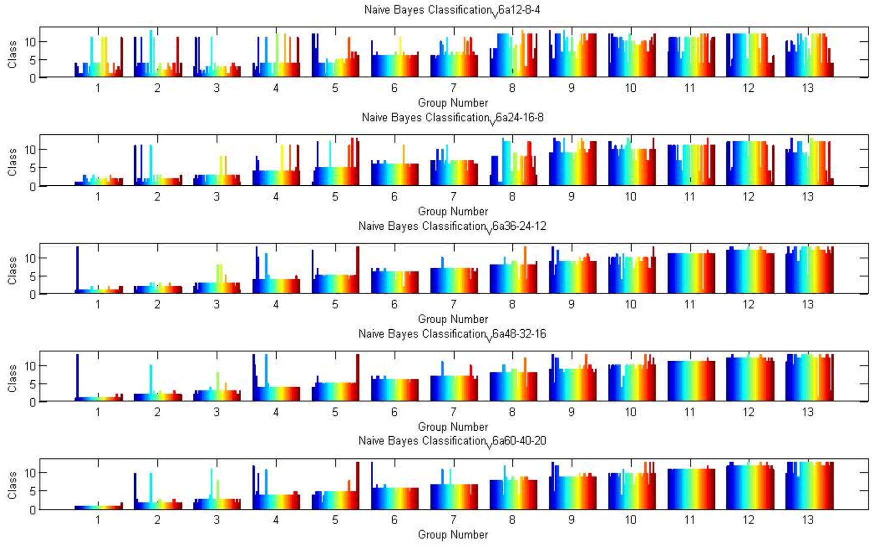


Figure 1. The six-story specimen at NCREE

Table 1. List of the 13 damage cases

Case Number	Second Stage Damage Group	Damage floors
1	Undamaged	None
2	Slight damage	1F
3		2F
4		3F
5		4F
6		5F
7		6F
8	Moderate damage	1F&2F
9		3F&4F
10		5F&6F
11	Severe damage	1F&2F&3F
12		2F&3F&4F
13		3F&4F&5F



Figuere 2. Independent testing result from ambient vibration of V6

Likelihood Selection

To assemble the optimal AR-ARX array for the SHM system , six of the thirteen damage cases were chosen, and the detail of the cases is shown in Table 2. The reasons for choosing these specific cases are described as follows: As the length of the AR-ARX array should be kept the same before and after the optimization process, the optimization strategy was decided to be selecting the best 16 coefficients from the 12 (4*3) combinations. The expression of how to form the final AR-ARX array is depicted in Figure 3. Meanwhile, since different structural characteristics can be reflected more easily when the damages are located in the lower level of the structure, the six cases with lower-story damage were focused. Following the designed process, the optimal 96-64-32 AR-ARX array was formed.

As mentioned before, totally 90 ambient vibration patterns with 20-second time history each were collected in the training database. That is, 1170 (90*13) AR-ARX arrays were transformed from the time history records and deposited for different sensors. To increase the robustness of the proposed SHM system, the velocity meters on the 4th, 5th, and 6th floor were used as the detection units.

Table 2. The four cases for likelihood selection

Case Number	Second Stage Damage Group	Damage floors

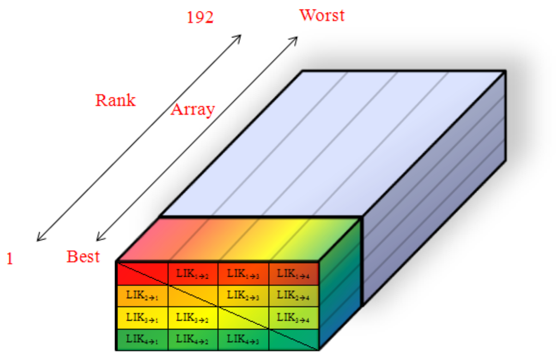


Figure 3. Expression of the optimization process from the 12ikelihood combinations

1	Undamaged	None
2	Slight damage	1F
4	Moderate damage	1F&2F
6	Severe damage	1F&2F&3F

As mentioned in the previous "likelihood" section, the array components with both large likelihood scores $LIK_{i\to j}$ and $LIK_{j\to i}$ where i and j represent different damage classes, in all the 12 combinations offer the strongest support to detect the possible existing damages on the structure. Namely, the 12 different likelihood scores are compared independently to optimize the AR-ARX array. A typical selection case of coefficients by the likelihood score of sensor V5 is shown in Table 3. Six different likelihood scores $LIK_{1\to 2}$ 、 $LIK_{1\to 3}$ 、 $LIK_{1\to 4}$ 、 $LIK_{2\to 1}$ 、 $LIK_{2\to 3}$ and $LIK_{2\to 4}$ are picked up to illustrate the detail of the likelihood selection concept. As indicated in the table, the calculated likelihood scores of array components 40 and 41 in $LIK_{2\to 1}$ are 54.40345 and 27.95874, which are relatively larger than the score of coefficients 39 and 42, as2.1233 and 2.053146 respectively. For the superior classification ability demonstrated by the likelihood score, these two components were selected to form the final optimized AR-ARX array. On the other hand, the likelihood scores of coefficient 25 are always relatively small when comparing to all the other component. This phenomenon demonstrates that structural characteristic under different damage conditions can not be reflected by coefficient 25, and all the array components with similar performance are carefully eliminated by the likelihood selection procedure.

Table 3. Demonstration example of likelihood score selection

Table 4. Demonstration example of likelihood score ranking

No. of pattern	38	39	**40**	41	42

$LIK_{1\to2}$	2.23712	22.97841	89.96941	147.5671	19.69415
$LIK_{1\to3}$	2.63377	23.25147	88.52593	78.76473	5.374351
$LIK_{1\to4}$	0.37254	17.04579	65.89551	26.63637	9.583765
$LIK_{2\to1}$	19.0049	2.1233	54.40345	27.95874	2.053146
$LIK_{2\to3}$	14.5312	10.6244	64.8015	23.02377	32.80946
$LIK_{2\to4}$	109.877	223.1202	802.8338	134.1232	64.80946

Rank	LIK	LIK	LIK	LIK	LIK	LIK
1	41	40	21	40	40	15
2	40	41	40	36	2	2
3	29	17	34	11	25	10
4	33	61	35	41	5	40
5	36	67	22	4	22	30
6	37	11	15	10	10	33
7	35	36	62	72	36	36

To clearly illustrate the concept of likelihood selection, the best seven coefficients of the 96-64-32 AR-ARX array selected by utilizing $LIK_{1\to2}$ 、$LIK_{1\to3}$ 、$LIK_{1\to4}$ 、$LIK_{2\to1}$ 、$LIK_{2\to3}$ and $LIK_{2\to4}$ among the 12 (4*3) combinations of sensor V6 are shown in Table 4. It is found that coefficient 40 was chosen six times which reflects the importance of this coefficient in this case. Similarly, coefficient 41 was also used three times to form the final AR-ARX array. By combining the best 16 coefficients in the 12 likelihood selection cases, the original 192 AR-ARX coefficients with equal weighting to every array component can be optimally organized again to obtain better SHM result.

The performance of the enhanced system was then verified and compared with the original system by 10 independent testing patterns. As the likelihood selection was conducted based on the 96-64-32 AR-ARX array, classification result with the same coefficient number is expressed. The accuracy and reliability of the SHM system before and after optimization is depicted in Figures 4 where some major enhancements are especially enlarged. It is investigated that the unexpected fluctuation can be largely improved by the optimized AR-ARX array. For example, the obvious spikes of sensor V6 in cases 2, 3, 5, 9, and 10 before the optimization are successfully suppressed by the new system. Alike phenomenon was also seen from the results of V5 in Figure 4. Moreover, the serious misclassification of class 2 of sensor 5, which indicates that the structure is under a “Slight” damage condition, was corrected by the new AR-ARX array. The trend that higher sensor can offer a better detection answer is kept in the new version of the SHM system. By rearranging the optimal coefficient sequence from comparing the different likelihood scores, the accuracy and consistency of the SHM system can be enhanced as desired. On the other hand, for the cases which can be correctly identified by the original AR-ARX array, the classification results will not be deteriorated by the optimization process. The robustness of the likelihood selection method is once again demonstrated.

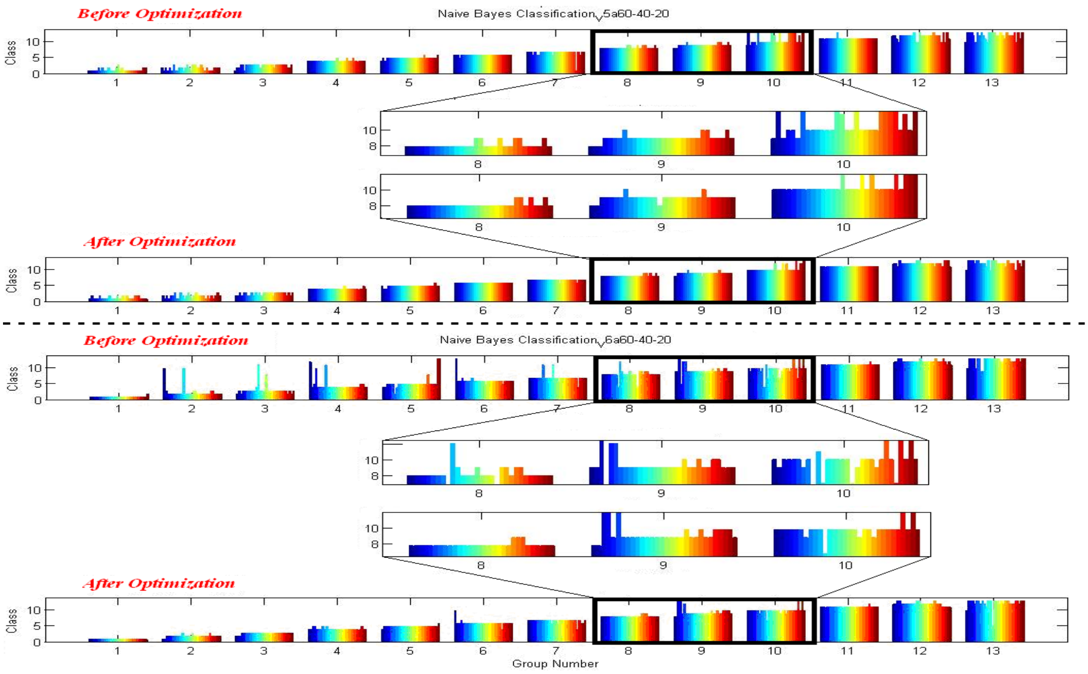


Figure 4. Classification results from the sensors on the 4th, 5th, and 6th floors before and after optimization

To improve the feasibility of the developed SHM system in practice, the concept of union in statistics was introduced into the system. For the observation trend that sensors on the higher floor may offer a better classification performance, the three sensors deployed on the 4th, 5th, and 6th floors were utilized as the input source, and the result of each event is filled with the union of the individual outcome from each sensor illustrated between the parentheses. The final decision was then obtained by these three respective values, and the consequences are listed in the last row of Table 5.

In order to verify the performance of the proposed SHM system in practice, the optimized system was tested by using three different events with an independent 20-second measurement each from the original database. Namely, a rapid and reliable result should be provided by the final SHM system within one minute, which is considered as a tolerable timing for pragmatic application. As shown in figures 5, the blue bars indicate the existing damage condition on the structure, and the brown bars show the detected damage condition from the SHM system. Only two misclassifications were found in the cases 2 and 9. The first event of “1F” in Table 1 is slightly classified as “2F”, and the second event of “3F&4F” is misplaced as “1F&2F”.

Satisfactory results were reached in all the other 37 cases by the proposed SHM system. Moreover, all the damage levels can be precisely described by utilizing the signal from the sensor on the 6th floor. The trend has shown that the accuracy of the SHM system with the optimized AR-ARX array can be upgraded to approximately 90% (35/39) and 95% (37/39). However, a system without 100% precision cannot be grouped as a successful system.

As shown in the Table, the SHM system can now provide a rapid damage evaluation within 1 minute (3X 20 sec). Accompanying with the introduction of union into the system, the “null” result may be concluded by the system. For example, the first event of damage class 2, the respective classifications are 2, 1, and 3 for sensors on the 4th, 5th, and 6th floors. According to the theory of union, no conclusion can be made by the system and the column was represented by the question mark. Similar phenomenon was also indicated in the second event of class 5, where damage occurred in the 4th floor. The classification results from sensors on the 4th, 5th, and 6th floors are 8, 7, and 5, respectively. Obviously, the system was confused by the first two misclassifications, and a question mark was filled again. Nevertheless, by introducing the concept of union again among the three separate events, the final result obtained by the union of the three 20-second events shown in the last column has demonstrated that the structural damage condition can now be perfectly indicated as the accuracy rate is raised from 90 to 95 % to 100 %.

A reliable classification performance among all the 13 cases operated within only one minute can be guaranteed by the integrated system. It is believed that the practical application of this developed system can be implemented easily on real structures in the near future.

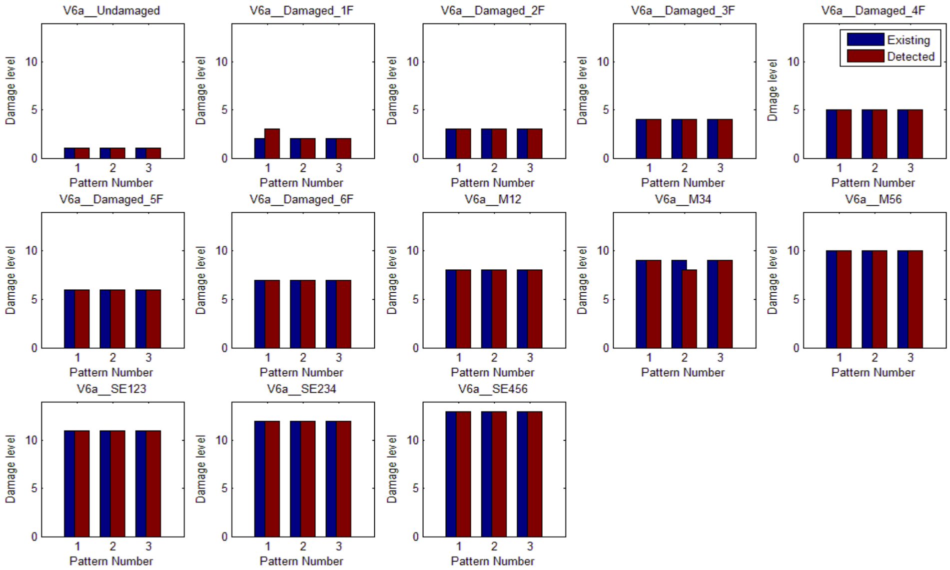


Figure 5. Practical Verification of three different events by the sensors on the 6th floor

Table 5. Verification of the final SHM system (V4∪V5∪V6)

Class	Event1	Event2	Event3	Final Result
1	1(1/1/1)	1(1/1/1)	1(1/1/1)	1
2	?(2/1/3)	2 (2/1/2)	2 (2/2/2)	2
3	3(3/3/3)	3 (3/3/3)	3 (3/3/3)	3
4	4(4/4/4)	4 (4/4/4)	4 (5/4/4)	4
5	5(5/5/5)	? (8/7/5)	5(5/5/5)	5
6	6(6/6/6)	6(6/6/6)	6 (7/6/6)	6
7	7(7/7/7)	7(7/3/7)	6 (6/6/7)	7
8	8(8/8/10)	8 (9/8/8)	8 (8/8/8)	8
9	9(9/9/9)	9(9/8/9)	9(9/9/9)	9
10	10(10/10/10)	10(10/10/10)	10(10/10/10)	10
11	11(11/11/11)	11(11/11/11)	11(11/11/11)	11
12	12(12/12/12)	12(12/12/12)	12(12/12/12)	12
13	13(13/13/13)	13(13/13/13)	13(13/11/13)	13

Summary and Conclusion

An ambient vibration based SHM system using the concept of AR-ARX array, Naïve Bayesian damage classification, and likelihood selection is proposed in this research. By using the ambient vibration data measured from three different floors of a scale-down six-story building located at NCREE, which can be easily achieved in our daily life, a specific data array was extracted and treated as the DNA array of the structure to form the SHM database. Based on the Naïve Bayesian damage classification, the coefficients obtained from any unknown damage case was compared with the individual mean values and standard deviations of the array in the precollected database of multiple damage conditions to detect the possible damage location and level of the structure. According to the experimental study, approximately 80% of the practical damage situation can be indicated by the structural monitoring system.

To improve the reliability of the system, the likelihood selection method was applied to optimize the data array of the structural health monitoring system. In order to keep the array size as the original detection system, which was decided to be in the form of 96-64-32, four of the thirteen damage cases were picked up, and the optimized data array was combined from the12(4*3) likelihood equations with the best 16 coefficients in each case. The damage conditions were then verified again by the optimized Bayesian classification method. It is evident that the stability of the SHM system can be successfully improved by the optimized data array. Unexpected fluctuation phenomena observed in the previous monitoring results were corrected and the accuracy of the system was improved to be 90-95%.Finally, SHM system was strengthened again by integrating the union concept to the system for practical application. The results from three sensors detecting the health condition of the structure in one minute strongly support the feasibility of the proposed system in practice.

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