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Study of the structural damage identification method based on multi-mode information fusion

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Abstract. Due to structural complicacy, structural health monitoring for civil engineering needs more accurate and effectual methods of damage identification. This study aims to import multi-source information fusion (MSIF) into structural damage diagnosis to improve the validity of damage detection. Firstly, the essential theory and applied mathematic methods of MSIF are introduced. And then, the structural damage identification method based on multi-mode information fusion is put forward. Later, on the basis of a numerical simulation of a concrete continuous box beam bridge, it is obviously indicated that the improved modal strain energy method based on multi-mode information fusion has nicer sensitivity to structural initial damage and favorable robusticity to noise. Compared with the classical modal strain energy method, this damage identification method needs much less modal information to detect structural initial damage. When the noise intensity is less than or equal to 10%, this method can identify structural initial damage well and truly. In a word, this structural damage identification method based on multi-mode information fusion has better effects of structural damage identification and good practicability to actual structures.

Keywords: multi-mode information fusion; structural damage identification; D-S evidence theory; sensitivity to damage; robusticity to noise.

1. Introduction

In common, most civil structures, including high-rise buildings, long-span bridges and so on, have a long service period, maybe several decades. As important structures are concerned, these periods may go to over one hundred years. During the whole life cycle, civil infrastructures endure long-term loading, fatigue effects, environmental corrosion or their couplings. Meanwhile, structural material performances will go to worse. Therefore, from the viewpoints of economics, serviceability and sustainability, it is necessary to conduct structural condition assessment and health monitoring

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to ensure the safety of these infrastructures under various damages. For the last twenty-five years, health monitoring of large-scale civil structures has received more and more attention in the field of civil engineering. Many researchers all over the world have been focusing on structural health monitoring (for short, SHM) and procured much achievements (Chen *et al.* 2004, Doebling and Farrar 1999, Yeung and Smith 2005).

Until now, a lot of structural health monitoring systems have been set up for diverse civil structures, such as Sunshine Skyway Bridge in Florida of the USA (Shahawy and Arocklasamy 1996) and Great Belt Bridge in Denmark (Xiao *et al.* 2005). In China, over last fifteen years a lot of long-span bridges have been built and structural health monitoring systems had been fixed on some of them. For example, Runyang Yangtse River Bridge is made up of two long-span bridges, the north cable-stayed bridge and the south suspension bridge. Runyang cable-stayed bridge has a main span of 406 meters. And Runyang suspension bridge, which is a continuous steel-box-beam bridge containing two towers and crosses the path of 1490 meters, is the longest suspension bridge in China and the third all over the world. In the structural health monitoring system for Runyang bridge, monitoring of the main cable vibration is involved as much as displacement, stress, temperature and vibration of the steel-box beam.

As well-known, structural health monitoring systems include a few basic modules, such as sensors, data transmission, structural damage identification, condition assessment and so on. Among them, the theory and realization method of structural damage identification play the key role. Static and vibrant data can be applied at first hand or transferred by mathematical methods to detect structural damages. But because the spatial scale is too large and loads vary with environmental and working conditions, static data can hardly be utilized to identify structural damages for long-span bridges and other complex civil structures. At the other hand, mass and stiffness are structural inherent parameters. When they change due to rust, crack, large displacements, fatigue etc., structural vibrant characteristics, such as frequencies, modal shapes and vibration energy, will shift in a certain direction. Therefore, varieties of these vibrant parameters can be used as a token of structural states. On the basis of this, the theory of structural damage identification based on vibration was put forward, which is a global method, on the contrary to local methods.

It is coincident that, when structural health monitoring draw more and more attention of researchers, the theory and technology of information fusion based on multi-sensor systems began to come into being. Initially, there were experts and specialists in military that played an important part of this field. At the beginning, data from many sensors were mixed and processed to track enemy planes, predict contrails and assess situations, and so the technique was named multi-sensor data fusion(for short, MSDF). From 1980's, MSDF technique was exported from military into automatic control, information processing and so on (Xiao *et al.* 2005). Afterwards, the concept of data fusion expanded continuously, and researchers found, objects that can be fused were not only data but also image, audio, symbol, vector and so on. So, multi-source (or multi-sensor) information fusion (for short, MSIF) came into being. MSIF is a new and developing technology, based on signal processing, pattern recognition, artificial intelligence, control theory, statistics, decision theory, information theory etc., and is the integration of many frontal mathematical methods(such as wavelet analysis, artificial neural network, fuzzy logic and so on) (Xiao *et al.* 2005, Steinberg *et al.* 1999). Simply, it is obvious that data to be fused from many sensors include more information than from single sensor. At the same time, structural health monitoring systems embody a lot of diversified sensors, which send off large numbers of data, signal and information everyday. Therefore, it is reasonable that MSIF is imported into structural health monitoring. In theory, the combination of MSIF and SHM can be realized not only in the parts of monitoring data pretreatment and damage detection but also in condition assessment.

The key of the global vibration-based damage identification methods is to establish damage vectors that may as well be sensitive to structural local damages and robust to noise around. It is obvious that structural vibrational parameters, such as natural frequencies, mode shapes and so on, can be taken directly as structural damage detection indices. At the other hand, wavelet analysis (Sun and Chang 2002), artificial neural network (Cho *et al.* 2004), genetic algorithm (Maity and Tripathy 2005), statistics (Fasel *et al.* 2005) and so on, yet can be applied to detect structural damages by transforming elementary parameters and responses.

It is natural that, modal information can be used as structural damage identification parameters. Many structural damage detection methods extract multi-mode information, such as modal strain energy, modal curvature and flexibility. In common, multi-mode information is averaged by mode amount in these methods. But in fact, actual results from averaging multi-mode information are not good occasionally. In the following portions of this paper, the structural damage identification method based on multi-mode information fusion will be put forward and analyzed in detail, and then through a numerical simulation the capacity of this method based on MSIF will be discussed.

2. Multi-source information fusion

The concept of data fusion was firstly proposed in America in the 1970's (Hall 1992). This technique was put forward to trace flight trails, identify enemies or friends and evaluate situation in military. With the rapid and remarkable development over twenty years, data fusion technique has been improved and enlarged to be multi-source information fusion for the reason of sensor technique advancing and computer technology developing. Due to its complexity, so far there has been no uniform definition of MSIF. Generally speaking, MSIF is a technique that uses computer to automatically analyze, integrate and utilize spatial-temporal multi-source information by certain rules, as a result of which it can achieve a consistent explanation and description of objects to be measured and thus competently fulfill the decision-making and evaluation tasks (Hall 1992).

2.1 Classifications of MSIF

Due to different levels of data abstraction, MSIF can be described as three classifications: data-level fusion, character-level fusion and decision-making level fusion. Different processing courses are taken to deal with different information (such as data musters, characteristic vectors and primary decisions) on diverse levels.

1. Data-level information fusion. It is the lowest classification of MSIF. As shown in Fig. 1, on this level data directly from sensors are imported into fusion centers, and then based on fusion results characters will be abstracted to identify objects to be observed. Owning to a bit of missing data to be dealt with, hairlike signals can not be provided to the next processing course. Therefore, the precision of characters abstracted is the highest. But, its limits are obvious: the amount of data is too large, so much data had to be delivered, and this process needs low anti-disturbing ability. So, data-level MSIF technique is always to be used in image compound, noise dismission of initial signals and so on.

2. Character-level information fusion. This is a middle level of MSIF. From Fig. 2, it is clear that

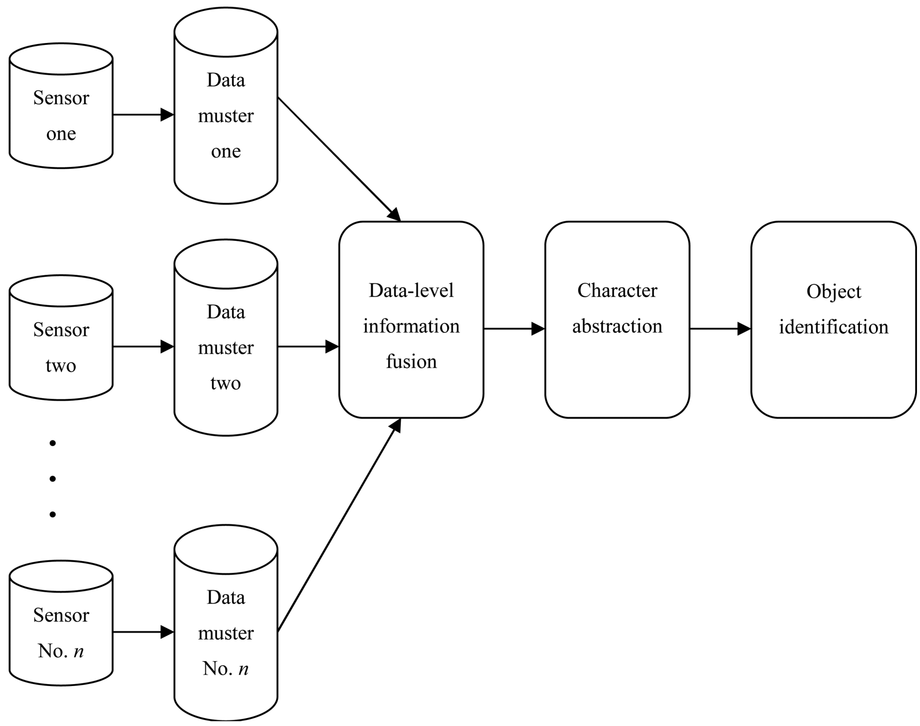


Fig. 1 Data-level information fusion

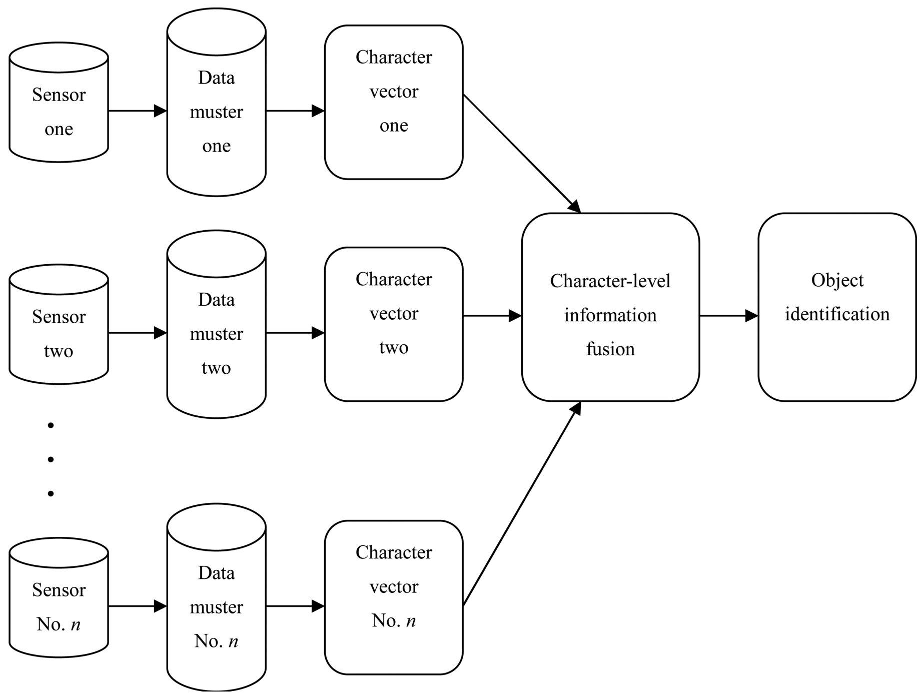


Fig. 2 Character-level information fusion

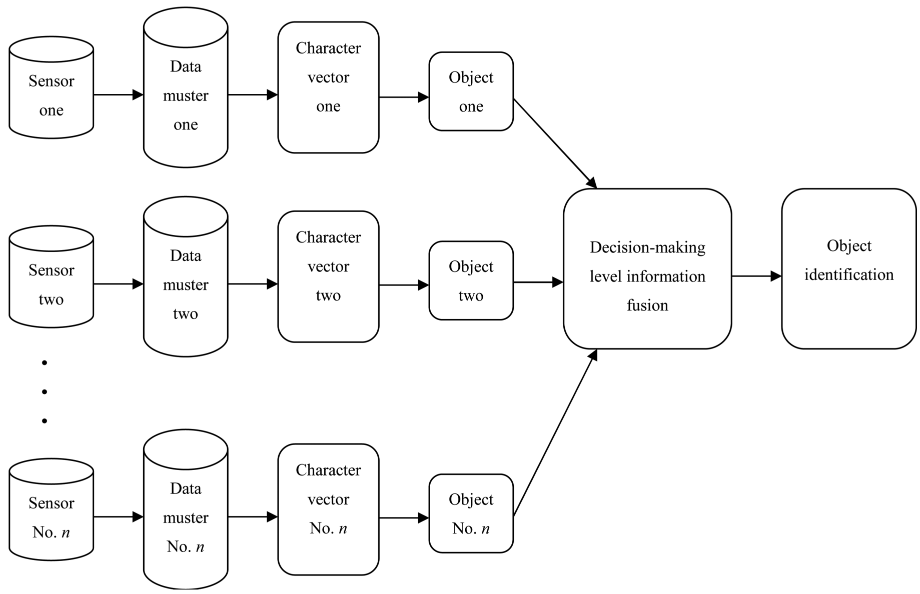


Fig. 3 Decision-making level information fusion

characters are firstly abstracted by means of data without fusion process. Subsequently, by forming character vectors to be taken into fusion centers, information fusion will be realized. Obviously, data to be dealt with on this classification are much less than on the first level. But on the other hand, loss of useful data will result in low performance of object identification by any possibility.

3. Decision-making level information fusion. Without question, it is the highest level of MSIF. The model of decision-making level fusion is described in Fig. 3. On this level, character vectors from data of different sensors are respectively taken as sources of decision-making. After medial determinations finished, information from them will be imported into fusion centers to produce the final decision. Only little amount of communications are needed on this level of MSIF, and types of sensors are hardly depended on, but in the process more data and information may be lost.

2.2 Mathematical methods of MSIF

As aforementioned, MSIF technology can be realized in virtue to many mathematical methods: signal processing and estimation, artificial intelligence, control theory, statistics, decision theory, information theory, geometry method and so on. Among them, D-S evidence theory is one of the most important methods for object identification and decision fusion.

Dempster and Shafer (Shafer 1976) brought forward evidence theory in the 1970's, which is an expanding development of the probability theory. Owing to setting up the corresponding connection of propositions and musters one by one, incertitude of propositions will be transferred to musters. Suppose $A_1, A_2, \ldots, A_n$ as n events, and $D_1, D_2, \ldots, D_m$ as m sensors, and $M_i(A_j)$ is the probability of the jth event occurring from the ith sensor. Then, the probability of the event P appearing is

$$M(P) = C^{-1} \sum_{\cap A_j = P} \prod_{1 \le i \le m} M_i(A_j) \tag{1}$$

where, $C = 1 - \sum_{\cap A_j = \phi} \prod_{1 \le i \le m} M_i(A_j) = \sum_{\cap A_j \ne \phi} \prod_{1 \le i \le m} M_i(A_j)$.

3. Structural damage identification method based on multi-mode information fusion

In this part, multi-source information fusion applied to structural damage identification will be discussed in detail. As aforementioned, three-level MSIF methods can be used in structural damage detection processes. In the following part, the structural damage identification method based on character-level MSIF will be analyzed through a concrete bridge numerical simulation. As well-known, multi-mode information averaged by mode amount is included in some structural damage methods. At the same time, MSIF technique is useful for multi-mode information processing. Therefore, the structural damage identification method based on multi-mode information fusion will be founded and discussed in detail in the following part.

Set the modal strain energy method as an example. Generally, structural damages results from structural stiffness loss, but not from mass loss. So, the element modal strain energy can be set up as a structural damage identification index. And then, respectively suppose the modal strain energy (for short, MSE) of the *j*th element with the *i*th mode of the initial structure and the damage structure as

$$MSE_{ij} = \{\Phi_i\}^T[K_j]\{\Phi_i\} \tag{2}$$

$$\text{and } MSE_{ij}^d = \{\Phi_i^d\}^T[K_j]\{\Phi_i^d\} \tag{3}$$

Where, the upper sign d expresses the damage structure, $[K_j]$ is the stiffness matrix of the *j*th element, and $\{\Phi_i\}$ is the *i*th modal shape of the structure. Because it is not known, the stiffness matrix of the damage structure will be replaced by it of the initial structure. Therefore, the modal strain energy change (for short, $MSEC_{ij}$) of the *j*th element with the *i*th mode is defined as

$$MSEC_{ij} = MSE_{ij}^d - MSE_{ij} = \{\Phi_i\}^T[K_j]\{\Delta\Phi_i\} \tag{4}$$

Whereupon, the structural modal strain energy change of the *j*th element with the *i*th mode is defined as

$$LMSEC_{ij} = \frac{|MSEC_{ij}^d - MSEC_{ij}|}{\sum_j |MSEC_{ij}^d - MSEC_{ij}|} \tag{5}$$

For noise dismission, information of m modes can be taken to identify structural damages as following

$$LMSEC_j = \frac{1}{m}\sum_{i=1}^{m} LMSEC_{ij} \tag{6}$$

This equation is the formula of the classical modal strain energy method. But in fact, entire mode information can hardly be measured and utilized, especially for large-scale civil structures, such as long-span bridges. At the same time, information of low-order modes is not the exact sign of structural states. So, for the purposes of gathering useful information from low-order modes and reducing noise effects, MSIF technique can be imported into structural damage identification. Subsequently, information of m modes is processed as Eq. (1), not averaged as Eq. (6). Therefore, the structural damage identification index based on modal strain energy and MSIF (using D-S evidence theory) is denoted as

$$LMSEC_p = C^{-1} \sum_{\cap j = P} \prod_{1 \le i \le m} LMSEC_{ij} \tag{7}$$

Where, $C = 1 - \sum_{\cap j = \phi} \prod_{1 \le i \le m} LMSEC_{ij} = \sum_{\cap j \ne \phi} \prod_{1 \le i \le m} LMSEC_{ij}$, and p is the sign of the pth element.

4. Numerical simulation

In this part, with a numerical simulation of a five-span concrete continuous box beam bridge the structural damage identification method based on multi-mode information fusion put forward in Chapter 3 will be analyzed and discussed in detail, including its capacity of damage diagnosis and robusticity to noise.

This concrete bridge, of a five-span prestressed box beam bridge, exists in the freeway from Beijing to Shanghai in China, every span of which crosses 30 meters. The transverse width of the bridge is 14 meters. Its main beam contains four boxes which are respectively single-box and single-cell and integrated into a composite section by transverse cast-in-place connecting strips. The typical section of this bridge is delivered in Fig. 4.

In the finite element model, the three-dimension beam element is taken to simulate the main beam and the top free degrees of bridge piers are coupled with the end of the main beam. Every

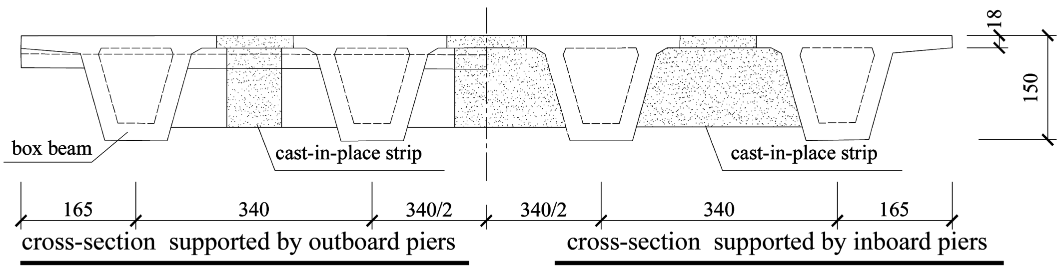


Fig. 4 Typical cross-section of the concrete continuous box beam bridge (unit: cm)

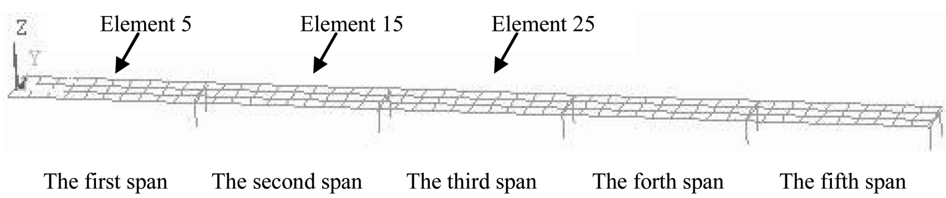


Fig. 5 Finite element model

Table 1 Damage cases

Damage case	Damage location	Extent of damage
1	Element 5, the middle of the first span	10%
2	Element 15, the middle of the second span	10%
3	Element 25, the middle of the third span	10%

box beam is divided into fifty elements by the lengthways direction of the bridge. That is to say, there are ten elements in every span of every box beam. So, the finite element model of this concrete bridge is set up to be as Fig. 5. Due to mechanical characteristics, the side beam of every span is the most disadvantage location for load. Therefore, element 5, 15 and 25, which are respectively the middle section of the side beam of the first span, the second span and the third span, are respectively supposed as a damage element. And then, damage cases are shown in Table 1.

4.1 Capacity to damage diagnosis

At first, analyze dynamic characteristics of the bridge and calculate the first 8 vertical modes. On the basis of these modes, damage identification results based on the classical modal strain energy method are obtained and shown in Fig. 6. From this figure, it is clear that damages of these three cases can hardly be detected by the classical modal stain energy method. That is because: ① With cast-in-place connecting strips, the four box beams are united into a whole beam and they are pressed synchronously. Hence, the bridge is holistic and little damage of the side beam effects structural whole stiffness very slightly. ② Elemental modal strain energies of the first 3 vertical modes of the damage case 1 are described in Fig. 7. From it, it is revealed that the elemental modal strain energy of every mode has diverse sensitivity to damages. Especially, some modal information is ever bad to damage identification as shown Fig. 7(c). Therefore, the processing method averaging multi-mode information as Eq. (6) maybe results in the sensitivity of the damage identification index declining. ③ For the purpose of nice damage identification results, it is necessary to receive smooth modal curves. But in fact, the elemental scale of this finite element model is comparatively large and the measurement spots for dynamic characteristics are distributed dispersedly. So, this is maybe a cause of bad effects of the classical modal stain energy method.

Modal information of the first two modes is taken to be imported into MSIF technique, and D-S evidence theory is looked upon as the rule of information fusion. Damage identification results based on MSIF are delivered in Fig. 8. From it, it’s obviously indicated that, with the help of MSIF to process multi-mode information the improved modal strain energy method has nicer sensitivity to structural damage. That is to say, all the three damage cases can be detected well by this improved structural damage identification method. Through D-S evidence theory, relative useful information can be abstracted to a more large extent and diverse states can be differed from each other by disparate function values. Therefore, information of only the first two modes to be used to damage identification have much nicer effects than eight modes of the classical modal stain energy method. So, it is clear that the improved modal strain energy method put forward in this paper has much more sensitivity to structural damage than the classical modal strain energy method, and initial damage of concrete continuous box beam bridges can be detected well and truly.

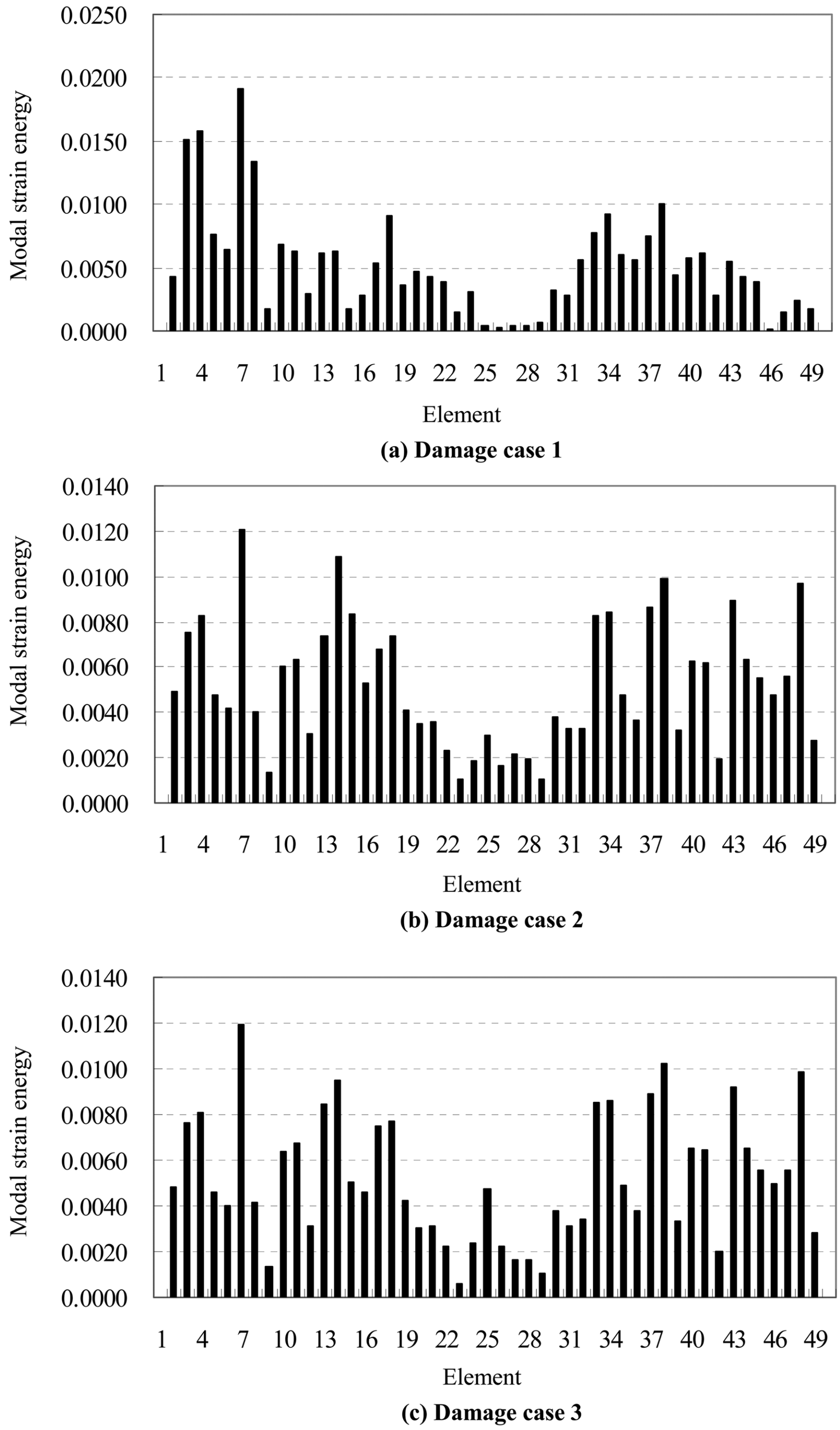


Fig. 6 Damage results of the classical modal strain energy method

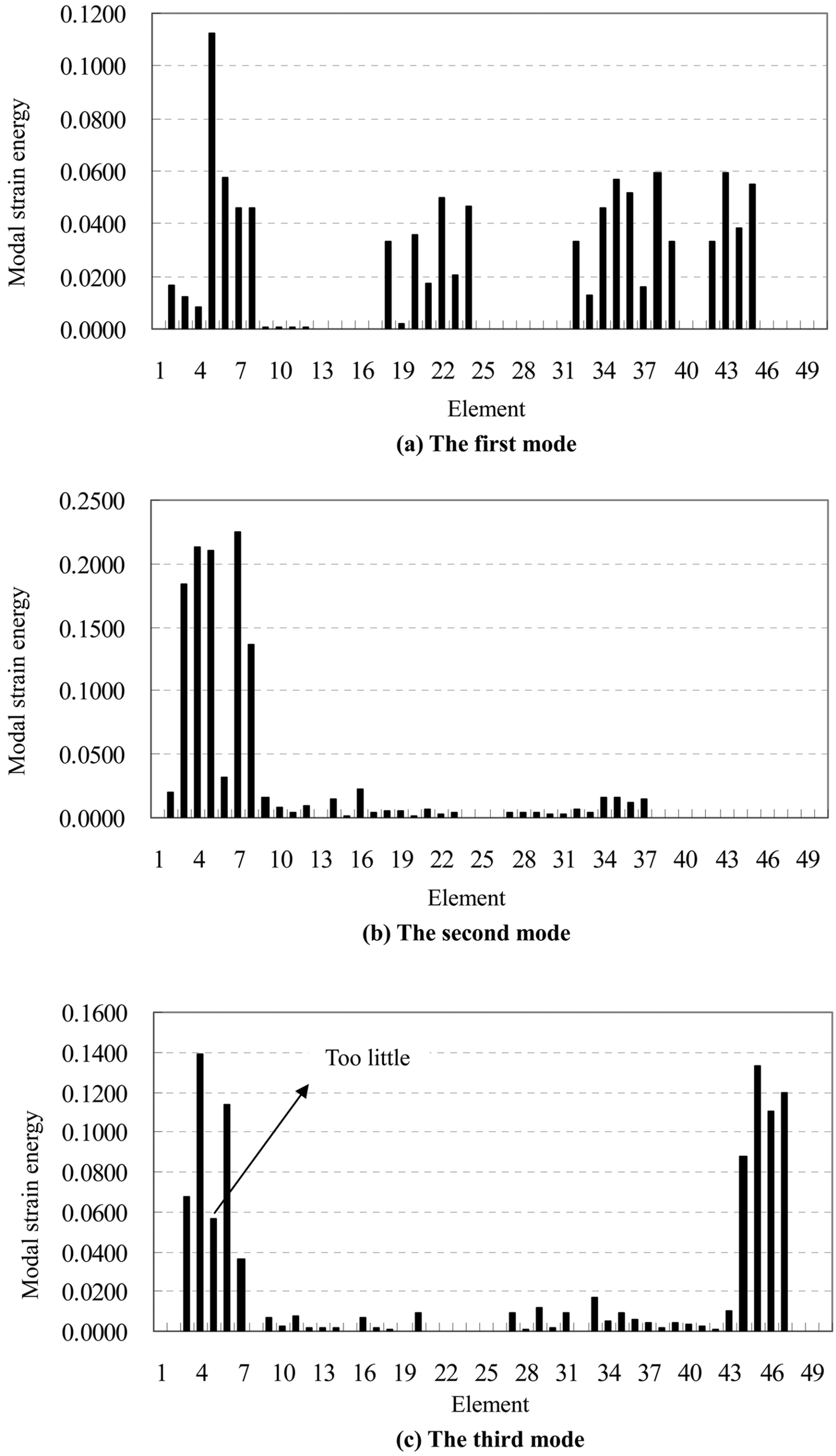
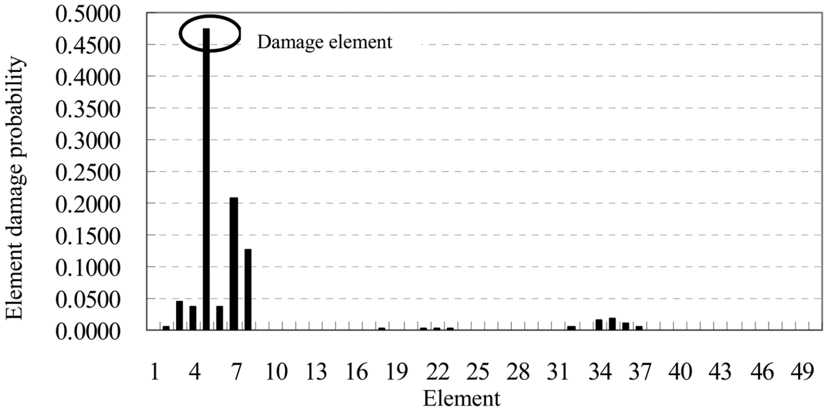
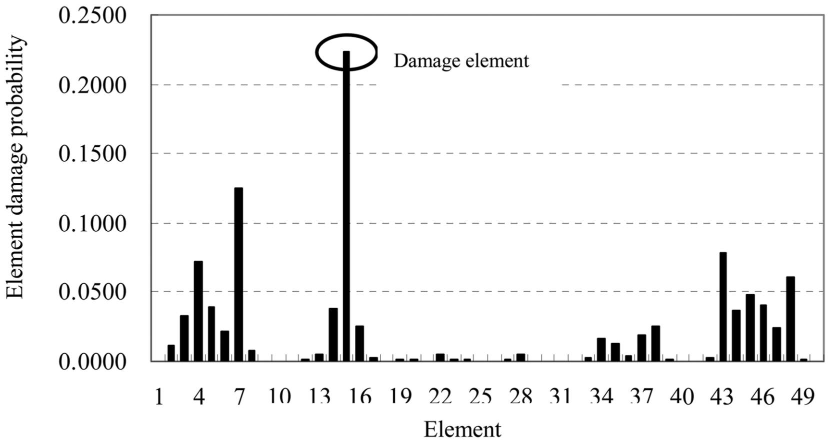


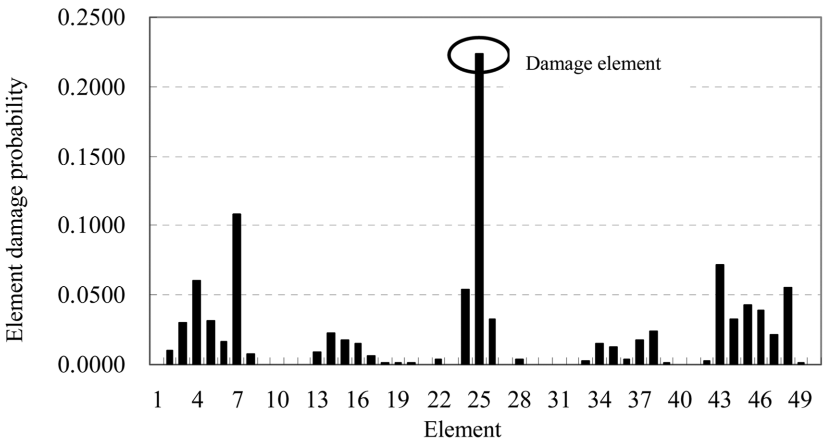
Fig. 7 Modal strain energies of the first 3 modes of the damage case 1



(a) Damage case 1



(b) Damage case 2



(c) Damage case 3

Fig. 8 Damage diagnosis results by the improved modal strain energy method

4.2 Robusticity to noise

One of the assessment indices for the practicability of structural damage identification methods is whether they have nicer robusticity to noise. So, in the next stage the robusticity of the improved modal strain energy method based on multi-mode information fusion will be discussed. Suppose the noise intensity *i* respectively as 1%, 5%, 10%, 15% and 20%. And then, noise will be added to modal information. With the damage case 1 taken as an example, all the five results of damage identification are described as Fig. 9 by the improved modal strain energy method. From this figure, it's revealed that, when the noise intensity is equal to or less than 10%, structural damages can be detected well by the improved modal strain energy method. Therefore, on the basis of MSIF, multi-mode information can be processed more availability than averaged as Eq. (6). That is to say, the improved modal strain energy method has not only nicer sensitivity to damage but also favorable robusticity to noise and can be applied to actual structural damage identification.

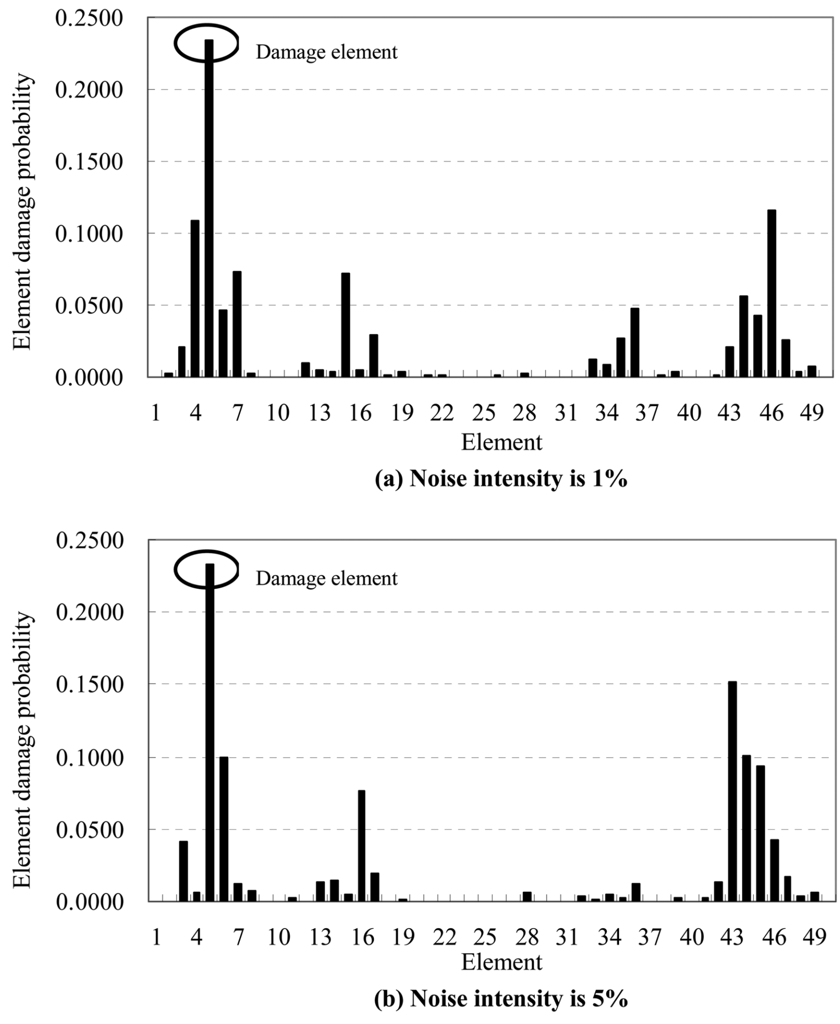
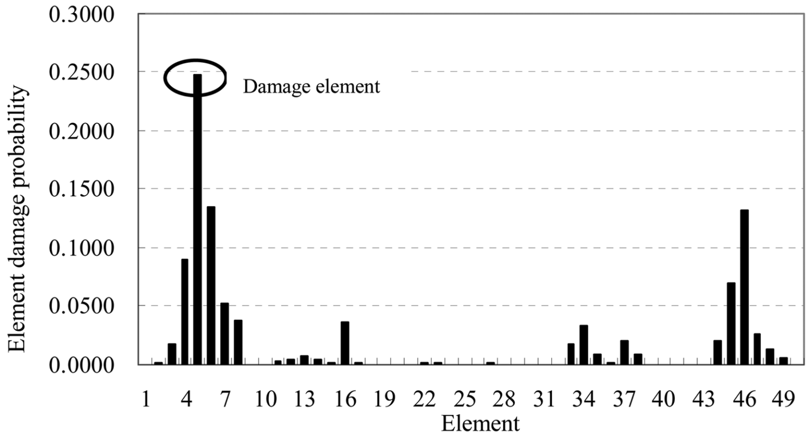
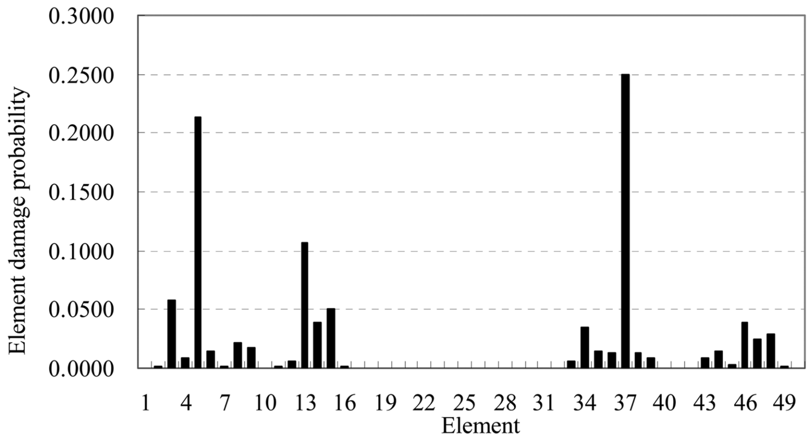


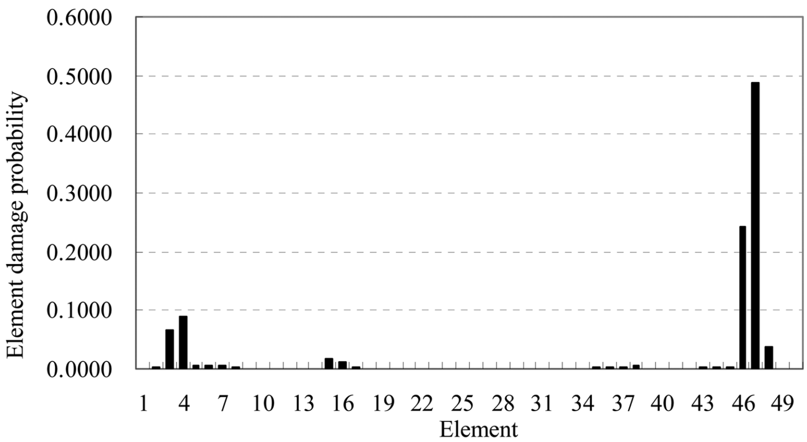
Fig. 9 Damage diagnosis results by the improved modal strain energy method based on MSIF under noise



(c) Noise intensity is 10%



(d) Noise intensity is 15%



(e) Noise intensity is 20%

Fig. 9 Continued

5. Conclusions

Multi-source information fusion, which is a developing mathematical method based on information science for the application to multi-sensor signal processing originally, has played an important part in military for twenty years and will be imported into civil fields. Information that can be fused with each other includes not only data from multi-sensor systems but also characteristic vectors about structural working states, especially maybe containing decision-making views. Combining characters of structural health monitoring systems with MSIF technique, it's obviously concluded that multi-source information fusion can be applied to structural health monitoring and structural damage diagnosis. In this paper, the essential theory and mathematical methods of MSIF applied into structural health monitoring are introduced firstly, and then the improved modal strain energy method based on multi-mode information fusion is put forward. Subsequently, with a numerical simulation of a concrete continuous box beam bridge the capacity of damage identification and robusticity to noise of this method are analyzed and discussed in detail. So, some important and practical conclusions are drawn as following:

1. It is feasible that multi-source information fusion is imported into structural damage diagnosis. After information fusion, the capacity of damage identification methods have been improved to a considerable extent.
2. Some structural damage identification methods need entire modal information, which can hardly been measured completely. Hence, in practice low-order modal information are averaged by mode amount to approximatively represent entire modes. But it is possible that this approach results in biggish errors. So, multi-source information fusion technique can be taken to process multi-mode information. Results of a numerical simulation about a five-span concrete continuous box beam bridge indicate that, the improved modal strain energy method based on multi-mode information fusion has nicer sensitivity to initial damages and robusticity to noise. In a word, this structure damage identification method put forward in this paper has good practicability to actual structures.

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