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An Information Optimizing Scheme for Damage Detection in Aircraft Structures

He Xufei[1], **Deng Zhongmin**[2] **and Song Zhitao**[1]

Abstract: This paper describes an information optimizing scheme which is developed by integrating rough set and hierarchical data fusion. The novel structural damage indices are extracted using the information from different sources and then imported into probabilistic neural network (PNN) for classification and health assessment. In order to enhance the accuracy of diagnosis, results from separate PNN classification are fused to achieve comprehensive decision. Rough set is employed to decrease the spatial dimension of data. The predictive accuracy of optimizing scheme is demonstrated on a helicopter, taken as an example, with varied sensors, for multiple damage identification.

Keywords: damage detection; wavelet energy; data fusion; rough set; neural network

1 Introduction

Structural damage detection (SDD) has received much attention in the field of aerospace engineering. Numerous techniques have been introduced for the damage detection of aircraft structures, among which the vibration based approaches have been widely exploited. These methods are based on the fact that any structure can be considered as a dynamic system with stiffness, mass and damping. Once some damages occur in the structure, the structural parameters will change, and the time-history response and modal parameters of the structural system will also shift. Thus, the change of the structural modal parameters or any other indices extracted from the responses can be taken as the indications of early damage occurrence in the structural system [Srinivas et al (2009); Yin et al (2009); Fadewar et al (2009); Long Qiao, Asad Esmaeily, Hani G. Melhem (2009); Ramana M. Pidapart (2006)].

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[1] Shanghai Aircraft Airworthiness Certification Center of CAAC, Shanghai, 200335,China
[2] Astronautics School, Beihang University, Beijing, 100191, China

However, multiple types of sensors like displacement, acceleration or strain sensors are required for the vibration signals acquisition and their measurements have varying degrees of uncertainty, which are difficult to determine [Kawchuk et al (2009); Ch. E. Katsikeros, G. N. Labeas (2009); Zengrong Wang, K.C.G. Ong (2010)]. For instance, the strain gauge is more local-oriented while the displacement and acceleration responses can reflect the overall condition of the structures. This is coupled with the practical reality of occasional sensor failure, greatly compromises the reliability and reduces the confidence in sensor data [Michel Studer, Kara Peters (2004)]. Also, during the real structural tests, only partial information can be obtained. Therefore, information optimizing is required to make the measured data from the numerous sensors ready for the damage detection.

Information optimizing scheme is a data mining and processing strategy, which integrates the signal acquisition, signal processing, feature extraction, feature fusion, attribution reduction, PNN damage identification and decision fusion. Normalized structural damage indices are constructed to make full use of varied sensor information. Multilevel data fusion and rough set method are two key techniques to SDD due to theirs inherent capabilities in extracting information from different sources and merging them into a consistent, accurate and intelligible data set without losing any important information.

Distinguished from many existing damage detection methods relying on certain specific sensor data, the information optimizing scheme makes full use of the multi-source information while effectively reducing the superfluous part and retaining the necessary features. Moreover, it can greatly increase the accuracy and reliability of damage detection. But up till now, there is not such a method on the integrated multilevel data fusion and rough set scheme which considers data from different sources.

This paper introduces an information optimizing strategy which can combine the data of strain, displacement response and modal characteristics. With distinctive indices extracted and condensed, fused damage decisions are achieved. For the validation of the scheme, an application on the structures of a helicopter is demonstrated.

2 Information optimizing techniques

The general idea of information optimizing scheme is to exploit the multi-source data through the techniques of hierarchical data fusion and rough set reduction, to obtain a consistent description of structural damage states. The brief concepts and forms of the technique are presented in the following paragraphs.

2.1 Data fusion

Data fusion is also called information fusion, which can combine data from multiple information sources, to achieve improved accuracies and more specific inferences than can be achieved by the use of a single source alone. According to the levels of data extraction in the course of fusion, data fusion can be categorized into data level fusion, feature level fusion and decision level fusion [Xiaofeng Liu, Lin Ma, Joseph Mathew (2009); Zhongqing Su, Xiaoming Wang, Li Cheng; Long Yu, Zhiping Chen (2009); Su et al (2007)].

Data level fusion. This is the basic level of data fusion where the raw data collected are summarized and analyzed. Data level fusion is the first utilization of the original data. It determines whether all of the important information is extracted or not. When dealing with different sources of data, various indices are needed. But owing to large amount of data to be processed, it leads to high cost and limited real time capability.

Feature level fusion. This is done after the raw data from multiple sensors are preprocessed and the indices are extracted. Then the feature information are inputted into certain classifier and drawn the fusion results. The merit of feature level fusion lies in the fact that it can compress large information set and also facilitates real time processing. Furthermore, the feature level information offered is directly related to decision-making. Thus the results can provide extra information for decision making to a great extent.

Decision level fusion is the highest level to provide the final result of three levels of fusion. As the fusion result has influence directly on decision level, appropriate fusion algorithms are employed to fuse the results from all classifiers and to produce the comprehensive final fusion results. Decision level data fusion is very flexible in processing information and can effectively reflect different kinds of non-synchronous information.

Different levels of fusion have their respective functions. Data level fusion is the basic step in the overall processing of data. Feature level and decision level fusion can be used to provide additional features to increase their recognition capabilities.

2.2 Rough set

Rough set theory is a new mathematical tool to handle uncertain and redundant data. It finds its applications primarily in the artificial intelligence and cognitive sciences, such as machine learning, knowledge discovery from databases, expert systems, inductive reasoning, automatic classification and pattern recognition. Due to its advantage of eliminating the need for additional information about data and the ability to extract rules directly from data set, this theory has been well studied by many researchers. The fundamental knowledge about Rough Set Theory [Zdzislaw Pawlak (2004)] is introduced as follows:

For an information system $S =< U,A,V,f >$ consists of: U—a nonempty, finite set called the *universe*; A—a nonempty, finite set of *attributes*, can be represented as $A = C \cup D$ with $C \cap D = \emptyset$, in which C is a finite set of *condition attributes* and D is a finite set of *decision attributes*; For each $q \in A$, namely A_q, A_q is called the domain of q; $f = U \times A \to V$ is an information function, which defines the attribute value of each element x, e.g., for every $q \in A_q, x \in U$, we get $f(x,q) = V_q$.

In an information system, to every subset of attributes $R \subseteq A$, a binary relation, denoted by *IND*(*R*), called the indiscernibility relation, is associated and defined as follows:

$$IND(R) = \left\{(x,y) \in U^2 : \forall r \in R, r(x) = r(y)\right\} \tag{1}$$

Where, *IND*(*R*) is an equivalence relation and $IND(R) = \bigcap_{r\in R} IND(r)$. Objects x, y satisfying relation *IND*(*R*).are indiscernible by attributes from *R*.

In this paper, a special case of information systems called *decision table* is discussed. In a decision table, the columns are labeled by attributes, and rows are labeled by events.

If $R \subseteq A$ and $X,Y \subseteq U$, then *R-lower* and *R-upper approximation* of X is defined respectively as:

$$R(X) = \cup\{Y \in U/IND(R) : Y \subseteq X\} \quad \bar{R}(X) = \cup\{Y \in U/IND(R) : Y \cap X \neq \emptyset\} \tag{2}$$

Where $U/IND(R)$ denotes the family of all equivalence classes of R.

If *IND*(*R*) =*IND*($R - r$), then the attribute r is superfluous, can be removed from decision table without losing any necessary information or affecting its discernment. One can find all possible minimal subsets of attributes, which lead to the same number of elementary sets as the whole set of attributes *reducts* and find the set of all indispensable attributes *core*, represents as *CORE*.

3 Damage detection process

Structural damage detection is a whole process of signal acquisition, preprocessing, information optimizing and results post-processing. An information optimizing scheme is proposed by integrating the techniques of hierarchical data fusion and rough set reduction, which are depicted in Fig.1.

Combined with data level fusion, multiple source data from strain, displacement, acceleration sensors are fused into features of strain energy, modal frequency, wavelet

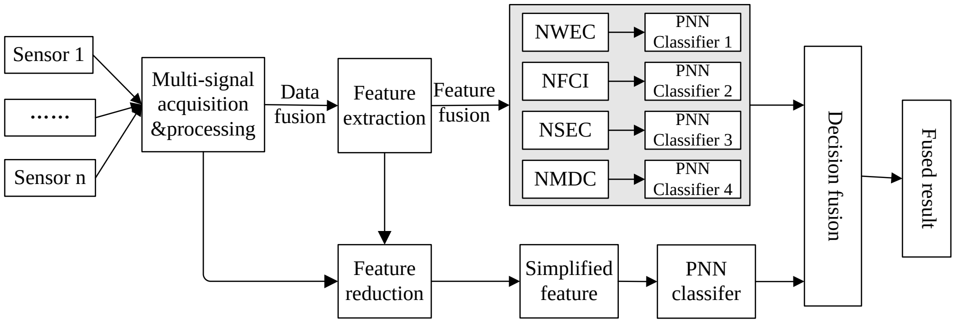

Figure 1: Roadmap of information optimizing scheme

energy and mixed strain energy-frequency index. The feature vectors are simplified and then imported into PNN classifier for fusion computation. Probability density function of each damage pattern would be derived from partial features respectively. Decision fusion is carried out based on the separate PNN classification results and damage would be localized.

3.1 Signal acquisition and processing

Different types of sensors are usually used in the structural damage monitoring test. There are displacement, acceleration and strain sensors. The raw measurement data are always affected by noise and measurement error due to precision of measurement facility, and operational skills of workers etc. Therefore, appropriate signal processing should be conducted like de-noise or smooth treatments.

3.2 Feature extraction

For structural damage detection, wavelet transform has become a preferred method in feature extraction of dynamic signals with its efficient time-frequency analysis, that is, wavelets can keep track of time and frequency information.

Through jth order wavelet packet transform with a mother wavelet function $\psi(t)$, the original signal $f(t)$ can be decomposed into

$$f_j(t) = \sum_{j,k=-\infty}^{\infty} c_{j,k}\psi_{j,k}(t) \tag{3}$$

And wavelet packet coefficients can be obtained

$$c_{j,k} = \int_{-\infty}^{\infty} f(t)\psi_{j,k}(t)dt \tag{4}$$

The energy index of the signal is calculated in different frequency segments. The wavelet energy index is defined as follows:

$$E(j,n) = \sum_{j=1}^{m} \sum_{k=0}^{n} c_{j,k}^2 \quad (m < 2^j) \tag{5}$$

Where j is the number of frequency segments and n is the maximal value of time sampling.

let $E_i = E(i,n)$,then normalized wavelet energy index is

$$NWEC_i = \frac{E_{di} - E_{ui}}{E_{ui}} \tag{6}$$

E_u, E_d are the wavelet energy of all frequency segments in the undamaged and damaged states.

Besides the NWEC index, the indices of normalized strain energy change index(NSEC), normalized frequency change index(NFCI) and normalized mixed damage change index(NMDC) are defined as bellow [Jiang, Zhang and Koh (2006); Jiang and Yao (2009)]

$$NSEC_i = \frac{SEC_i(k)}{\sum_{j=1}^{n} |SEC_j(k)|} \tag{7}$$

$$NFCI_i = \frac{FCI_i}{\sum_{j=1}^{m} |FCI_j|} \tag{8}$$

$$NMDC_i = \frac{MDC_i(k)}{\sum_{j=1}^{n} |MDC_j(k)|} \tag{9}$$

where $SEC_i = \frac{\{SE_{di}\}-\{SE_{ui}\}}{\{SE_{ui}\}}$, $FCI_i = \frac{f_{di}-f_{ui}}{f_{ui}}$ and $MDC_i = \frac{\{SE_{di}\}-\{SE_{ui}\}}{f_{di}^2-f_{ui}^2}$ are strain energy change ratio, modal frequency change ration and mixed damage index of ith mode respectively; n is the total number of measured nodes, m is the mode number; f_{ui}, f_{di} are the frequencies of the ith mode in the undamaged and damaged states; $\{SE_{ui}\}$ and $\{SE_{di}\}$ are the strain energy vector of the ith mode in the undamaged and damaged states.

Through data fusion of original sensors information, the indices of *NWEC*, *NSEC*, *NFCI* and *NMDC* are obtained. These four indices interpret the signals from different sides and can well reflect the health state of structures.

3.3 Feature fusion

With the inherent characteristics of nonlinear function mapping and learning ability, neural network algorithm has attracted a lot of attention for the structural damage detection. Here, the probabilistic neural network is chosen as the damage patterns classifier.

In 1990, Specht [Specht (1990)] firstly introduced the feed-forward PNN including three layers: input layer, pattern layer and output layer. The PNN describes measurement data in a Bayesian probabilistic approach, which implements the Parzen window to represent the probability density functions of the known data sets, and then judges the pattern class of damage types to which the testing vectors of unknown source should belong. The standard probabilistic density function of class q at point X is

$$f_q(X) = \frac{1}{n_q (2\pi)^{p/2} \sigma^p} \sum_{i=1}^{n_p} \exp\left[\frac{(X - X_{qi})^T (X - X_{qi})}{2\sigma^2}\right] \tag{10}$$

Where, n_q is the number of training vectors in class q; p is the dimensionality of the training vectors; X_{qi} is the ith training vector for class q; σ is the smoothing factor.

Through the probabilistic density function $f_q(X)$, the probability of every partial of input features is estimated separately. With the computed probability values of input features, they are classified to different classes. The above process demonstrates the mechanism of PNN mapping. Then the weighted average method is employed for decision fusion computation, where the probability values corresponding to each class of the previous PNN is used. With the available $f_{q,j}(X)$ for class θ_q and jth sensor, a fused probabilistic density function $\bar{f}_q(X)$ is given by

$$\bar{f}_q(X) = \sum_{j=1}^{m} w_{q,j} * f_{q,j}(X) \tag{11}$$

Whereas $w_{q,j}$ is the normalized weighting coefficient for class θ_q and jth sensor.

The weighting coefficient reflects the confidence level for each sensor and is determined by the identification accuracy of PNN classifier in the training phase, and $\sum_{j=1}^{m} w_{q,j} = 1$.

3.4 Decision making

For the final classification, a clear judgment of X assigned to which class of θ_q must be achieved. The fused decision results from PNN present the probabilistic density function along all the output classes. Adopting majority voting technique, the class with the maximal probabilistic density is considered the target one. If X belongs to

θ_q, the probability $\theta_q(X)$ is set to100% while the others are set to zeroes. This is the quite winner-take-all principle [13]

$$\theta_q(X) = \begin{cases} 1, & \max(f_q(X)) \\ 0, others \end{cases} \qquad (q = 1, 2, \cdots No_{output}) \tag{12}$$

4 Numerical simulation

For an initial demonstration of the improvement in damage identification due to multi-source information optimizing, we consider a coaxial helicopter FH-1(shown in Fig.2). Damage scenarios are simulated by reducing the stiffness of each brace. The fuselage structures in undamaged condition and other six damage patterns are analyzed, as listed in Tab 1. There are two damage magnitudes of 20% and 40%, combining three states of different locations.

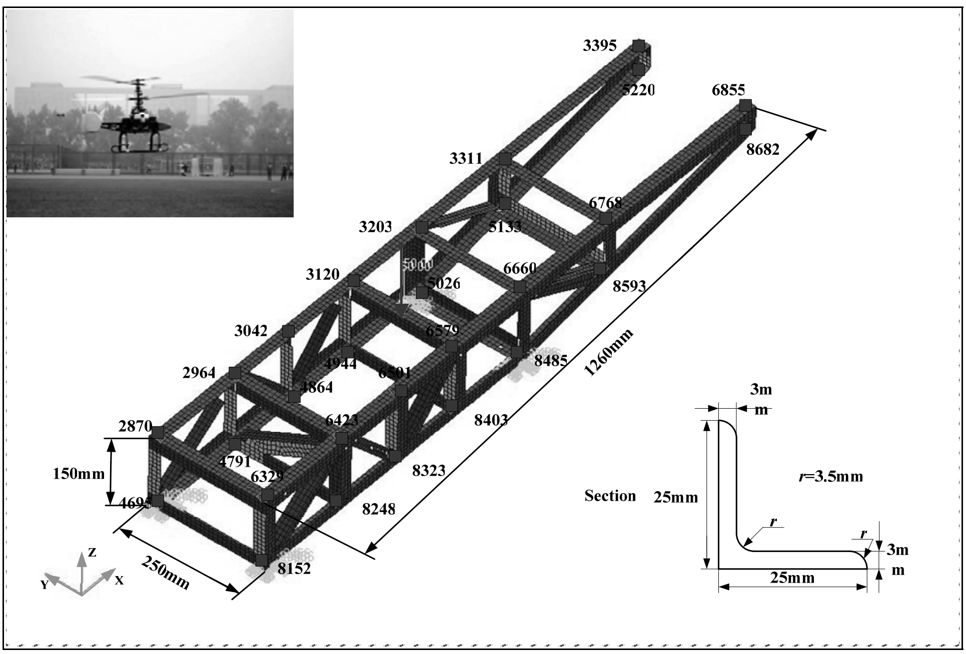

Figure 2: FH-1 helicopter and FE model of fuselage

4.1 Dynamic simulation and feature extraction

Finite element model of the helicopter's fuselage is firstly established with 2D shell element. Twenty one element types with different material parameters and shell thickness are defined. Simulations are performed in MSC/NASTRAN including normal mode analysis and transient response analysis. Normal mode analysis is conducted to extract the modal frequencies and the normalized strain for each mode. Once with major modal frequencies and strain energy available, we can calculate the indices of *NSEC*, *NFCI* and *NMDC* respectively by the Eq.7 to Eq.9. These data are then used as the input for further damage detection scheme.

To obtain the time-history response of fuselage structures, transient response analysis for fuselage in healthy and damaged condition is carried out. According to the real forms of fuselage structures, complete constraints (all six degree of freedom are constrained) are added to 16 nodes like node 4685, 4686, 4693, 4694(Fig.2), where the undercarriage is connected to the body. A force of sinusoidal function was applied in the middle of brace 3120-6579 so as to simulate the excitation imposed on the fuselage, which is induced by rotor wing at a rated rotating speed 1200 RPM. The amplitude of the force is $100\sin(2\pi \cdot 40 \cdot t)N$ and its duration is 2 seconds with a time interval of 0.001s. Responses are collected at a sampling frequency of 1000 Hertz. When the displacement responses are imported into the Eq.3 to Eq.6, the vector of wavelet energy change are computed.

Table 1: Damage patterns of fuselage structures

Pattern Class	Damage Severity	Damage Location
Pattern 1	Stiffness reduced by 20%	Brace 6423-8323 and brace 6579-8323 are damaged
Pattern 2	Stiffness reduced by 40%	Brace 6423-8323 and brace 6579-8323 are damaged
Pattern 3	Stiffness reduced by 20%	Brace 6423-8323 and brace 6660-8593 are damaged
Pattern 4	Stiffness reduced by 40%	Brace 6423-8323 and brace 6660-8593 are damaged
Pattern 5	Stiffness reduced by 20%	Brace 4791-6423,3203-5133 ,and 6660-8593 are damaged
Pattern 6	Stiffness reduced by 40%	Brace 4791-6423,3203-5133 ,and 6660-8593 are damaged

4.2 Fusion computation

For the PNN classification, much training and testing data are required. Also, it is a fact that the measured data are always contaminated by noise. As a result, random noise is added to the input of PNN. Here, the extracted features for healthy and all the damage scenarios are disturbed by noise as follows

$$S_i = S_i^o \times (1 + \varepsilon R) \tag{13}$$

Where, S_i is the ith component of indices (*NWEC, NFCI*, *NSEC* and *NMDC*) contaminated by noise; S_i^o is the ith component of original indices without noise; R is the random sequence of standardized normal distribution; ε is the relative noise level.

For each damage scenario, an input vector$IN_{1\times 11}$, $IN_{1\times 9}$, $IN_{1\times 10}$ or $IN_{1\times 10}$ is constructed with the four indices. For *NWEC,* there are 11 components at 11 nodes-node 6329, 6378, 6423, 6501, 6579, 6629, 6660, 6768, 6915, 6902 and 6855. *NFCI* contains 9 components for the first 10 modes except the second mode. For *NSEC* and *NMDC*, each has 10 components corresponding to the first 10 modes.

$$IN = [NWEC, NFCI, NSEC, NMDC]_{1\times 40} \tag{14}$$

By Eq.13, a particular 200×40 noise matrix is established. Multiplying each row of noise matrix with the *IN*, 200 sets of input data are created, of which the first 100 rows are used to train PNN classifier and the other 100 rows are for testing. Consequently, a 600×40 training vector and another 600×40 testing vector are produced for all damage scenarios.

The training vectors are taken as the input of PNN classifier. Each column of the input vector corresponds to an attribute. Thus, the number of neurons in the input layer is 40. While each sample of the input vector is set as one neuron in the pattern layer, resulting in a number of 600 neurons. Neurons in the output layer are related to the damage patterns, so the number is 6. With a framework of 40-600-6 and smoothing factor 0.1, PNN is trained. After that, testing vector is imported and the probabilistic density function of each pattern is estimated, of which the largest one indicates the damage class.

Tab.2 demonstrates the results of PNN identification with the input data polluted at a noise level of ε=0.08. The inputs of each single index and data fusion state are considered. It can be seen that the identification accuracy (IA) is low for the pattern 1 to 4, compared that the pattern 5 and 6 can be fully identified. Particularly, the identification results are better by using all of the four indices (40 attributes) than using single index alone. From Fig.3, we can see that the samples of Pattern 1 and Pattern 2 are misclassified with each other, which is the same between Pattern 3 and

Pattern 4. That is because the damage of Pattern 1 and 2 occur at the same location (brace 6423-8323 and 6579-8323) only with different damage severity. For the trained PNN classifier, the testing feature vectors of Pattern 1 and 2 are similar to each other, misclassification may happen. Despite of that, the total largest error is less than 13% by the single index. It is also the same reason for Pattern 3 and 4 with the damage in the brace 6423-8323 and 6660-8593. Damage of Pattern5 and 6 are in three braces of the fuselage parts, distinguishing themselves with other patterns. As a result, these two patterns can be identified without any error. These results demonstrate the effectiveness of the neural network classification.

From Tab. 3 and Fig. 4, it is clear that the total identification accuracy decrease with the increase of the noise level. But the identification accuracy is higher than 90.3% with all indices, even when the noise level is as high as 0.1. It not only suggests that the PNN classifiers are noise resistant, but also the extracted indices are appropriate for the damage identification.

When the damage detection results from single index are computed separately, Eq.11 can be adopted for the decision fusion. Probabilistic density functions from different PNN classifiers are fused by weighting coefficient $w_{q,j}$. As the training outputs of the four PNN classifiers are appointed, the normalized coefficient $w_{q,j}$ is set to 0.25. The final result of fused decision is shown in Tab. 2.

A significant improvement of identification accuracy can be observed after decision fusion, which is clear for the first four patterns. Almost all the patterns can be exactly identified and the total IA rises up to 99.2% at a noise level of 0.08. The damaged patterns can be identified with a high confidence, not less than 98% for every sample. That is because the decision fusion makes full use of the original multi-source information. And the probabilistic density function achieves the maximum considering all of the previous classification results. The comprehensive results of data fusion can represent the original information better compared with ones obtained by single PNN classifier. This indicates that the hierarchical data fusions with data level fusion (extract novel features), feature level fusion (PNN classification) and decision fusion together have good capability of damage detection and anti-noise ability.

4.3 Reduction analysis

From above discussion of the single PNN classifier, some samples are not well identified when using all the indices. A major reason for it is that some sensor information is not coincided, while some information is superfluous affecting the computation efficiency. Rough set reduction can be carried out with the K-means clustering and core set extraction from universal feature set. KMEANS function

Table 2: Identification results for PNN classifier with noise level ε=0.08

Identified Accuracy/%	Data used of matrix *IN*					
	1-40	1-11	12-20	21-30	31-40	Data fusion
Pattern 1	94	91	82	68	99	98
Pattern 2	92	92	73	88	98	98
Pattern 3	96	89	90	93	67	100
Pattern 4	85	90	82	96	85	99
Pattern 5	100	100	100	100	100	100
Pattern 6	100	100	100	100	100	100
Total IA	94.5	93.7	87.8	90.8	91.5	99.2

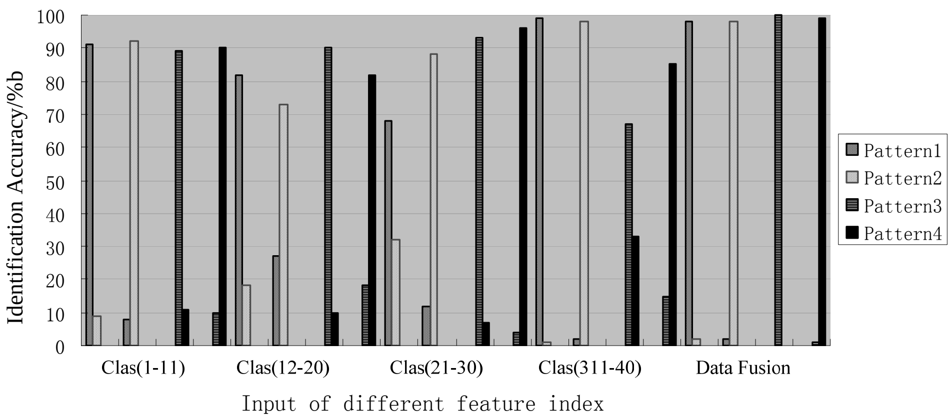

Figure 3: Identification results by using different index data (ε=0.08). (Note: The Pattern 5 and 6 are fully identified and their results are not plotted in the figure above.)

partitions data into mutually exclusive clusters, and returns the index of the cluster to which it has assigned each observation. Unlike hierarchical clustering, k-means clustering operates on actual observations (rather than the larger set of dissimilarity measures), and creates a single level of clusters. The distinctions mean that k-means clustering is often more suitable than hierarchical clustering for large amounts of data.

By a similar way as fusion computation, the input vectors for PNN classifiers are created at a noise level from 0.06 to 0.1. KMEANS function is firstly used for the clustering of input vectors and all the samples are classified into 5 clusters.

Then, A decision table is determined by 40 condition attributes $NWEC_1$, $NWEC_2$, $\ldots$, $NWEC_{11}$; $NFCI_1$, $\ldots$, $NFCI_9$; $NWEC_1$, $NWEC_2$, $\ldots$, $NWEC_{10}$; $NMDC_1$,$\ldots$, $NMDC_{10}$ and one decision condition to define 6 damage patterns. Attribute reduction is conducted; resulting in a core set 1-17. The first 17 attributes $NWEC_1$, $NWEC_2, \ldots, NWEC_{11}$; $NFCI_1, \ldots, NFCI_6$ are the core ones and cannot be reduced and others are superfluous. This implies that the wavelet energy index combined with modal frequency index are more sensitive to the structural damage, the extracted features have advantages over the simple index used by Jiang, Zhang and Koh (2006); Jiang and Yao (2009). Now, the new input vectors are constructed by the core attributes in different noise levels. Through a newly built 17-600-6 size PNN, decision results are computed and shown in Tab. 3 and Fig. 4.

It is shown that, the patterns can be effectively identified by PNN classifier using the core feature set. The lowest identification accuracy for single pattern is 87% and the total one is 90.3%, when the noise level is $\varepsilon = 0.1$. For the noise level at 0.06, 0.07, 0.08 and 0.09, the total identification accuracy is 99.7%, 98.3%, 97%and 95.8% respectively. It is obvious that the identification accuracy decrease with the noise level rises.

Fig.4 and Fig.5 give the identified results with and without rough set reduction in different noise level. It is noted that rough set reduction can improve the identification accuracy up to 2.1% higher after rough set reduction at the noise level of 0.06. And when the noise level ε is 0.09, the identification accuracy increases the most, by 4.5%. This verifies that the rough set reduction method can not only effectively reduce the spatial dimension of multi-source information and retain the necessary features, but also it can greatly increase the accuracy and reliability of damage detection.

Table 3: Identification results before and after attribute reduction in different noise level

Identified Accuracy (IA)/%	Noise level and data used of matrix *IN*									
	0.06		0.07		0.08		0.09		0.1	
	1-40	1-17	1-40	1-17	1-40	1-17	1-40	1-17	1-40	1-17
Pattern 1	99	99	97	97	94	91	91	88	89	87
Pattern 2	100	99	92	97	92	94	90	95	89	90
Pattern 3	95	100	94	99	96	100	86	95	81	96
Pattern 4	93	100	88	97	85	97	81	97	82	93
Pattern 5	100	100	100	100	100	100	100	100	100	100
Pattern 6	100	100	100	100	100	100	100	100	100	100
Total IA	97.8	99.7	95.2	98.3	94.5	97.0	91.3	95.8	90.3	94.3

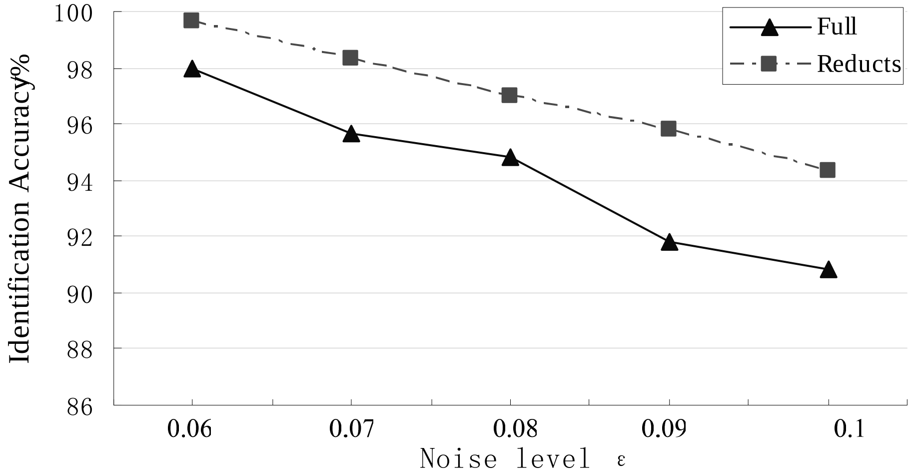

Figure 4: Identification results from all and reducts input in different noise level

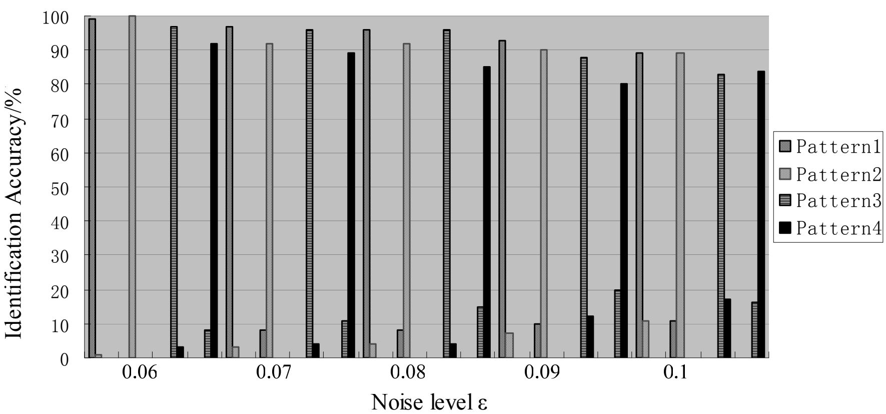

Figure 5: Identification results in different noise level for all input

5 Conclusion

By integrating hierarchical data fusion and rough set reduction techniques, an information optimizing scheme is introduced in this paper. The proposed approach can make full use of multi-source sensor information while decreasing the spatial dimension of feature attributes. From its application to the damage detection of helicopter structures, the following conclusions can be drawn:

1) With multilevel data fusion, the information optimizing scheme extracts various features from the sensor data, making sure that all the important sensor information is utilized. The novel indices like Wavelet Energy Change index and Normalized Multi Damage Change index describes the structural condition in an all-round way.

2) Decision fusion of the proposed scheme has better damage detection capability than single PNN classifier. It improves the accuracy of damage identification, which is no less than 98% at a noise level of 0.08.

3) Attributes reduction by rough set can significantly reduce the numbers of PNN input neurons. Thus, the complexity of PNN is decreased and the time for samples training and testing is reduced. Furthermore, the damage identification using the condensed attributes can achieve higher IA than using all the features.

4) The proposed damage detection scheme has strong anti-interference ability. The total identification accuracy is 90.3% for all features input even at a noise level as high as 0.1.

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