ANFIS-2D Wavelet Transform Approach to Structural Damage Identification

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Abstract— **In this paper, a structural damage identification approach is proposed combining adaptive network-based fuzzy inference system (ANFIS) and 2D wavelet transform (2D WT) technologies. The approach is referred to as ANFIS-2D-WT. First, measured structure vibration response signals from multiple sensors are arranged as a 2D image signal. Then, 2D WT is applied with a twofold objective, perform sensor data fusion and work as a feature extractor. After 2D WT is applied, the energy distribution in different frequency bands of the resultant sub-2D signals is calculated. Based on its energy percentage contribution, selected elements of the obtained feature vector are taken as inputs for the ANFIS. The output of the ANFIS is a condition index, which can be a Boolean value (0 or 1) for level 1 damage assessment use (damage detection), or a number of values for level 2 damage assessment use (damage localisation). Provided an ANFIS model is well trained by the available data, it can be used for health monitoring and damage localisation. The proposed approach was applied to the data obtained from an experiment involving a cantilever beam for damage detection and localisation. The testing results show that the method is successful in detecting and classifying structural damage even in the presence of noise.**

Index Terms—**ANFIS, 2D Wavelet transform, Structural damage detection, Structural damage identification.**

I. INTRODUCTION

Damage in structural and mechanical systems is defined as *"changes to the material and/or geometric properties of these systems, including changes to the boundary conditions and system connectivity, which adversely affect the current or future performance of these systems"* [1]. For safety reasons and because of the economic benefits that can result, the interest in the ability to detect and locate structural damage at the earliest possible stage is pervasive throughout the civil and aerospace engineering communities.

Damage identification methods can be classified into four levels of damage assessment [2]: level 1 (detection): determination that damage is present in the structure; level 2 (localisation): level 1 plus determination of the geometric location of the damage; level 3 (quantification): level 2 plus quantification of the severity of the damage; level 4 (prediction): level 3 plus prediction of the remaining service life of the structure.

The objective of this study is to develop methods for structural damage detection and localisation (SDDL) (i.e. level 1 and level 2 damage assessments) based on the 2D WT and ANFIS technologies. The work of this paper is organised as follows. Section II discusses the utilisation of 2D WT as sensor data fusion and feature extractor methodology for structural damage identification. Then, in section III, the ANFIS-2D-WT approach to structural damage identification is presented. The effectiveness of the proposed method is demonstrated in section IV by analysing the vibration response data from a cantilever beam. Concluding remarks are given in section V.

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II. SENSOR DATA FUSION AND FEATURE EXTRACTION USING 2D WT

In previous approaches to SDDL, as those reported in [4-7], the Wavelet Transform (WT) or Wavelet Packet Transform (WPT) component energies are used as the feature vector to detect structural damage. However, a drawback in those approaches is that one feature vector is extracted for one sensor. In applications where multiple sensors are used, the information from each sensor needs to be integrated in some way. The previously proposed 1D wavelet/wavelet packet methods could not efficiently group the information of many sensors.

In this work, a novel method of using ANFIS for damage classification and 2D WT for sensor fusion and feature extraction in SDDL is introduced. The 2D WT provides an efficient and natural way to integrate the information of multiple sensors and thus makes the structural damage identification more reliable and efficient compared with 1D WT/WPT methods.

A. *Two-dimensional wavelet transform (2D WT)*

The 2D WT representation is a straightforward generalisation of the 1D wavelet representation [8]. As in 1D, a 2D signal $f(x,y)$ could also be represented in terms of wavelet families. One difference between the 2D wavelet in comparison with the 1D version is that all the signals in these wavelet families are 2D signals. In 1D wavelets, the mother wavelet family is generated by a basic wavelet function, i.e. a mother wavelet $\psi(t)$, and the father wavelet family is generated by another basic wavelet function, i.e. a father

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wavelet $\varphi(t)$ [3]. Similarly, in 2D wavelets, wavelet families can also be generated from basic 2D wavelet functions. These basic 2D wavelet functions can be constructed by taking the tensor product (denoted as '$\otimes$' in the following equations) of a horizontal basic 1D wavelet function and a vertical basic 1D wavelet function. This leads to four different types of 2D basic wavelet functions:

$$\begin{aligned}\Phi(x,y) &= \varphi_h(x)\otimes\varphi_v(y)\\ &= \textit{horizontal father} \otimes \textit{vertical father} \qquad \text{(1a)}\\ \Psi^v(x,y) &= \psi_h(x)\otimes\varphi_v(y)\\ &= \textit{horizontal mother} \otimes \textit{vertical father} \qquad \text{(1b)}\\ \Psi^h(x,y) &= \varphi_h(x)\otimes\psi_v(y)\\ &= \textit{horizontal father} \otimes \textit{vertical mother} \qquad \text{(1c)}\\ \Psi^d(x,y) &= \psi_h(x)\otimes\psi_v(y)\\ &= \textit{horizontal mother} \otimes \textit{vertical mother} \qquad \text{(1d)}\end{aligned}$$

From (1), the basic 2D wavelet functions include one father wavelet and three mother wavelets. The corresponding four 2D wavelet families { $\Phi_{m,n}(x,y)$ }, { $\Psi^v_{j,m,n}(x,y)$, $j\ge 0$ }, { $\Psi^h_{j,m,n}(x,y)$, $j\ge 0$ } and { $\Psi^d_{j,m,n}(x,y)$, $j\ge 0$ } are generated by scaling and translating these four basic 2D wavelet functions as follows:

$$\Phi_{m,n}(x,y) = \Phi(x-m,\ \ y-n) \qquad (2a)$$

$$\Psi^v_{j,m,n}(x,y) = 2^{-j}\Psi^v(2^{-j}x-m,\ \ 2^{-j}y-n) \qquad (2b)$$

$$\Psi^h_{j,m,n}(x,y) = 2^{-j}\Psi^h(2^{-j}x-m,\ \ 2^{-j}y-n) \qquad (2c)$$

$$\Psi^d_{j,m,n}(x,y) = 2^{-j}\Psi^d(2^{-j}x-m,\ \ 2^{-j}y-n) \qquad (2d)$$

As with 1D wavelets, the father wavelet family is good at representing the smooth part and the mother wavelets are good at representing the detail. In 2D wavelets, the father wavelet family { $\Phi_{m,n}(x,y)$ } is used to describe the smooth part of $f(x,y)$, three mother wavelet families, { $\Psi^v_{j,m,n}(x,y)$, $j\ge 0$ }, { $\Psi^h_{j,m,n}(x,y)$, $j\ge 0$ } and { $\Psi^d_{j,m,n}(x,y)$, $j\ge 0$ } are used to capture the vertical detail, the horizontal detail, and the diagonal detail of $f(x,y)$, respectively.

B. Sensor data fusion and feature extraction using 2D-WT

The main idea of using 2D WT as sensor fusion and feature extraction mechanism in SDDL is as follows: the vibration structural response measured by one sensor i is a vector denoted as

$$f_i(t) = \left[f_i(t_1) \quad f_i(t_2) \quad \ldots \quad f_i(t_n)\right]^T \qquad (3)$$

where n denotes the sampling number.

Without losing generality, it is assumed that m sensors (from sensor 1 to sensor m) are used. Thus, there are m vibration response vectors { $f_1(t)$, $f_2(t)$ … $f_m(t)$ }. If these vectors are concatenated along rows and the result denoted as F , it gives:

$$F = \left[f_1(t) \quad f_2(t) \quad \ldots \quad f_m(t)\right] \qquad (4)$$

F is an n-by-m matrix and can be seen as a 2D signal, or as an image. A certain column of this image represents the response at all n measured samples from a certain sensor and a certain row of this image represents the responses of all the m sensors at a particular sample time. This image F includes the information of all the sensors throughout the measurement duration and therefore gives a whole picture describing the dynamic behaviour of that system. Therefore, if the 2D WT is applied to image F , then its important features can be revealed. Subsequently these features can be used to train an ANFIS for damage assessment.

Therefore, a feature vector can be formulated in the following way: at L- level 2D WT, the original 2D signal (image) F is decomposed into L+3L sub-2D signals (images): i.e. A_1 , D_1^v , D_1^h , D_1^d , for a level 1 decomposition. The energy of a discrete signal $x=[x_1,x_2...x_N]^T$ is defined as the sum of its squared modulus:

$$\varepsilon_x \overset{def}{=} \sum_{n=1}^{N} \left|x_n\right|^2 \qquad (5)$$

The ratio of energy of the $L+3L$ sub-signals from F is then defined as:

$$V = \left[\frac{\varepsilon_1}{\varepsilon_f}, \frac{\varepsilon_2}{\varepsilon_f} .... \frac{\varepsilon_{L+3L}}{\varepsilon_f}\right] \qquad (6)$$

where ε_1 , ε_2 , … ε_{L+3L} are defined by equation (5), by arranging the 2D signal as a 1D signal, denoting the energy of the sub-signals obtained from the 2D WT. The term ε_f is the energy of the original signal F.

Note that (6) is not directly used as the feature vector. Instead, some sub-signals are selected and their percentages are calculated to form the feature vector. The selection is based on the following two criteria: 1) The sub-signals selected should be significant sub-signals contributing large energy percentages in F. The reason for this criterion lies in the fact that the insignificant sub-signals generated by wavelet transform are normally contributing to noise and should be removed. Empirically, it is assumed that a sub-signal is significant if its ratio of energy contribution to the original signal is no less than 3%. 2) The sub-signals selected should be sensitive to the damage. Damage usually has different effects on different frequency bands. Hence different sub-signals have different sensitivities to damage. By selecting the sub-signals sensitive to the damage, it is guaranteed that the damage could be effectively captured. The sensitivity analysis can be derived either by finite element model analysis of the structure (analytical method) or by prior experiments (experimental method). For convenience, in this study only the significant sub-signals are chosen to form the feature vector.

Having chosen the energy percentage vector as the feature, the procedures for damage identification depend on the availability of the *a-priori* data. In an 'unsupervised learning mode', where data are only available from the undamaged structure, damage identification methods are based on feature comparison: two features, one extracted from the system in undamaged condition and the other from the current system, are compared in some way to obtain the damage indicator. The damage indicator is then compared to some threshold value and the conclusion about if the structure has deviated from the reference condition is obtained. On the other hand, in a 'supervised learning mode', where data from a system in different structural conditions (including the undamaged and some damaged conditions) are known in advance, the damage identification techniques are based on pattern classification: a database including models of the structure in different conditions is established using feature vectors for the *a-priori* data sets. Given a new data set which is to be classified as one of the conditions of the system, the task is to search through the database for the model which gives the best fit to the data. The corresponding condition of this database model is then applied to the data.

III. ANFIS-2D-WT Structural Damage Identification

A structural damage assessment method combining 2D WT with ANFIS is proposed in this section. This method is called ANFIS-2D-WT method. The procedures of the method include the following five steps: 1) Determine the architecture of the ANFIS (the reader interested in a full explanation of ANFIS is referred to [9]). The architecture includes: a) the number of input variables, b) the number of linguistic values for each input variable, c) the type of Membership Functions (MFs) for each input linguistic value, d) the number of output variables, e) the number of linguistic values for each output variable, and f) the type of MFs for each output linguistic value. 2) Determine the rules for the ANFIS. 3) Prepare the training data sets (containing the input and desired output data pairs) for the ANFIS. 4) ANFIS training using the training data sets. 5) Pass the new data through the trained ANFIS and the damage information of the new data is obtained.

The steps above are detailed as follows. The number of all possible conditions for the system is $r+1$ (one healthy condition denoted as D_0 and r damaged conditions $D_1 \sim D_r$). For each condition, and considering all the sensors, a total of N 2D measurement data, or images, are available. This results altogether in $(r+1)\times N$ image data sets and they are arranged as a data matrix:

$$Data \quad Matrix = \begin{bmatrix} \{y^{D_0-1}\}, & \{y^{D_0-2}\}, & \ldots & \{y^{D_0-N}\} \\ \{y^{D_1-1}\}, & \{y^{D_1-2}\}, & \ldots & \{y^{D_1-N}\} \\ . & . & . & . \\ . & . & . & . \\ \{y^{D_r-1}\}, & \{y^{D_r-2}\}, & \ldots & \{y^{D_r-N}\} \end{bmatrix} \tag{7}$$

where $\{y^{D_j-i}\}$ ($i=1...N$, $j=0...r$) are output measurement data from the i^{th} test at condition D_j (a 2D signal, considered as an image). Each row of the matrix contains all the available data sets for a certain condition.

Select a typical measurement 2D signal (image) $\{y\}$ in the data matrix (7) and perform 2D WT analysis on it. The original 2D signal $\{y\}$ is decomposed into a number of sub-2D signals, from which p sub-2D signals are selected and the energy percentages of these sub-signals are calculated. In the current study, these energy percentages of the selected sub-signals are the inputs to the ANFIS model. Therefore, the number of input variables to the ANFIS is p. Three linguistic values characterised using linguistic terms as 'small', 'medium' and 'large' are defined for each of the p input variables. The type of these MFs for these linguistic values is 'bell-shape' and defined by:

$$\mu_s(x) = \frac{1}{1 + \left| \dfrac{x - c_i}{a_i} \right|^{2b_i}} \tag{8}$$

There is only one output variable defined in the ANFIS: the structural condition. It is normally represented by a condition index for convenience. A zero-order Sugeno fuzzy model has been adopted in the ANFIS structure, which means that singleton values are defined for the output variable and the type of the corresponding MF is a distinct constant.

So far, only the architecture of the ANFIS model has been determined: It contains p inputs (corresponding to p energy percentages) and one output (condition index). Each input variable has 'small', 'medium' and 'large' linguistic values characterised by three bell-shape MFs. The number of ANFIS rules is determined by the combination of linguistic values for the input variables. For p input variables, each with three linguistic values, the number of resultant combinations is 3^p. Correspondingly, the number of rules is 3^p. For example, assume only two sub-signals are selected ($p=2$). The two input variables and one output variable are denoted respectively as x_1, x_2 and z. For each input variable, three linguistic values denoted as { $M_1^{x_1}$, $M_2^{x_1}$, $M_3^{x_1}$ } (for x_1) and { $M_1^{x_2}$, $M_2^{x_2}$, $M_3^{x_2}$ } (for x_2) are defined. Therefore, a total of nine rules are contained in the ANFIS model:

Rule 1. If x_1 is $M_1^{x_1}$ *and* x_2 is $M_1^{x_2}$, then z is d_1
Rule 2. If x_1 is $M_1^{x_1}$ *and* x_2 is $M_2^{x_2}$, then z is d_2
Rule 3. If x_1 is $M_1^{x_1}$ *and* x_2 is $M_3^{x_2}$, then z is d_3
Rule 4. If x_1 is $M_2^{x_1}$ *and* x_2 is $M_1^{x_2}$, then z is d_4
....
Rule 9. If x_1 is $M_3^{x_1}$ and x_2 is $M_3^{x_2}$, then z is d_9

Having determined the ANFIS architecture and the rules, it is necessary to prepare data sets for training use. For each available output data $\{y^{D_j-i}\}$ ($i=1...N$, $j=0...r$) in the data matrix (7), perform the same 2D WT analysis as were done on the typical $\{y\}$ and the same p sub-signals are selected. Their energy percentages are arranged as a vector denoted as Per^{D_j-i}. This procedure is applied to all the data set in (7) and an Energy Percentage Matrix (EPM) is obtained:

$$EPM(2D\ WT) = \begin{bmatrix} \{Per^{D_0-1}\}, & \{Per^{D_0-2}\}, & \ldots & \{Per^{D_0-N}\} \\ \{Per^{D_1-1}\}, & \{Per^{D_1-2}\}, & \ldots & \{Per^{D_1-N}\} \\ . & . & . & . \\ . & . & . & . \\ \{Per^{D_r-1}\}, & \{Per^{D_r-2}\}, & \ldots & \{Per^{D_r-N}\} \end{bmatrix} \quad (9)$$

The vector $\{Per^{D_j-i}\}$, containing p elements, is taken as an input vector for the ANFIS. Matrix (9) contains a total of $(r+1)\times N$ such input vectors for ANFIS. They are used as training data for ANFIS. The current ANFIS use a supervised learning algorithm, which means the target output for each input vector is needed. It has been mentioned that the output is the structural condition represented by a condition index. Depending on the level of damage assessment conducted, different output index patterns are adopted. If the ANFIS is used only to identify damage occurrence (level 1 damage assessment), the output indices are Boolean values (0 for healthy condition D_0, 1 for damaged cases $D_1 \sim D_r$). In this situation, the data matrix (9) contains a total of $(r+1)\times N$ input and desired output data pairs:

$$Data\ \ Matrix(Level\ \ 1) = \begin{bmatrix} \{Per^{D_0-1},\ 0\}, & \{Per^{D_0-2},\ 0\}, & \ldots & \{Per^{D_0-N},\ 0\} \\ \{Per^{D_1-1},\ 1\}, & \{Per^{D_1-2},\ 1\}, & \ldots & \{Per^{D_1-N},\ 1\} \\ . & . & . & . \\ . & . & . & . \\ \{Per^{D_r-1},\ 1\}, & \{Per^{D_r-2},\ 1\}, & \ldots & \{Per^{D_r-N},\ 1\} \end{bmatrix} (10)$$

If the ANFIS is used for the damage localisation (level 2 damage assessment), a total of $r+1$ condition indices each corresponding to a structural condition need to be defined. Defining j as the index for condition D_j, the data matrix containing the input and desired output data pairs is:

$$Data\ \ Matrix(Level\ \ 2) = \begin{bmatrix} \{Per^{D_0-1},\ 0\}, & \{Per^{D_0-2},\ 0\}, & \ldots & \{Per^{D_0-N},\ 0\} \\ \{Per^{D_1-1},\ 1\}, & \{Per^{D_1-2},\ 1\}, & \ldots & \{Per^{D_1-N},\ 1\} \\ . & . & . & . \\ . & . & . & . \\ \{Per^{D_r-1},\ r\}, & \{Per^{D_r-2},\ r\}, & \ldots & \{Per^{D_r-N},\ r\} \end{bmatrix} (11)$$

Data matrices (10) and (11), are used, respectively, for training two ANFIS with two different levels of damage assessment.

The next step is ANFIS training. The number of the premise parameters to be determined is $3\times3\times p$. This comes from the fact that for each of the p input variables, we use three MFs each decided by three premise parameters (a, b and c in (8)). The number of the consequent parameters to be determined is 3^p. The ANFIS architecture uses a hybrid learning algorithm [9] to estimate these $9p+3^p$ premise parameters all together with the consequent parameters.

After the ANFIS model has been well trained, this ANFIS model can be used to find out the structure condition for new data. Given new data, the same 2D WT is performed and the same p sub-signals are selected. The energy percentages of these selected sub-signals are used as inputs to the trained ANFIS. The condition for the new data can be seen from the output (condition index) of the ANFIS.

Note that by using the 2D WT, all information is preserved (the measurements from m sensors are all used at once). Advantageously, only one ANFIS is established and needs to be trained, differing from previous approaches where a different artificial neural network needs to be trained for every sensor.

IV. APPLICATION TO A CANTILEVER BEAM

In this research, an experimental study involving shaker-excited vibration tests of an aluminium cantilever beam was carried out in the laboratory. The beam is 90cm length and cross section 2.545 × 0.647cm. Zero-mean band-limited (0~500Hz) Gaussian white noise was used as the input signal to the amplifier. The amplifier gain was controlled manually and the shaker provided an approximately 10 N peak, via a random force input to the beam. A force gauge screwed on the bottom surface of the beam was used to directly measure the input. The shaker was attached with this force transducer through a stinger. Fig. 1 shows the experimental setup.

Six accelerometers (7g each) were screwed to the top surface along the centreline at selected positions (15cm, 30cm, 45cm, 60cm, 75cm, 90cm from the left fixed point, respectively). The data from each test came from these 6 accelerometers and 1 force transducer. The data were collected at a sampling rate of 10kHz for a duration of 4 seconds.

Five damage scenarios (E1~E5) were simulated by adding a lumped mass (22g) at 30cm, 45cm, 60cm, 75cm, and 90cm, respectively (see Fig. 1.). A summary of the experimental damage conditions is provided in Table 1

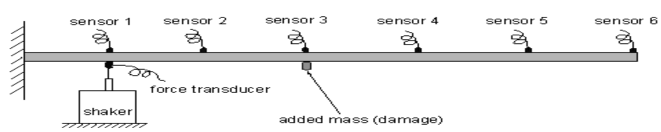

Fig. 1. Cantilever beam for experiment

TABLE I
SUMMARY OF DAMAGE CASE E1~E5

Damage Case	Location of Damage	Damage Description
E1	30cm	adding a lumped mass of 22g
E2	45cm	adding a lumped mass of 22g
E3	60cm	adding a lumped mass of 22g
E4	75cm	adding a lumped mass of 22g
E5	90cm	adding a lumped mass of 22g

A. ANFIS-2D-WT method results

The experiment was repeatedly carried out under each of the six possible conditions of the system. The system response data and the corresponding condition were recorded during the test. From each condition, 20 test data are used, within which the first 10 are for the training use and the remaining 10 are for the testing use. Therefore, altogether there are available 60 training data sets and 60 test data sets.

The response data are not used directly in the ANFIS model. First, the measurements from all six sensors in each test are arranged as a matrix (image). Then, two-level db3 2D-WT is performed on this matrix. From the obtained seven sub-signals (images), three are selected, the ones with the higher energy percentage values, and these energy percentages are taken as the inputs for an ANFIS. Two ANFIS models, ANFIS1 and ANFIS2 are established. ANFIS1 is used to identify damage occurrence (level 1 damage assessment) while ANFIS2 is used for damage localisation (level 2 damage assessment). The architecture of these two ANFIS models is the same, but they produce different output values. ANFIS1 is only used to distinguish healthy and damaged conditions; therefore the output is a Boolean value (0 for healthy, 1 for damaged). The output of ANFIS2 needs to differentiate all the possible conditions and hence it is defined as a numerical value j ($j = 0 \sim 5$), where j corresponds to damage condition D_j .

The mapping surface between the three inputs and one output of the trained ANFIS1 is shown in Fig. 2. Fig. 3 shows the results when applying the trained ANFIS1 to the testing data. The testing error of ANFIS1 is 2.7567e-5.

Fig. 4 shows the mapping surface of the ANFIS2 model. The testing result of the trained ANFIS2 model is shown in Fig. 5. We can see that the testing error of the ANFIS2 model is 0.0021.

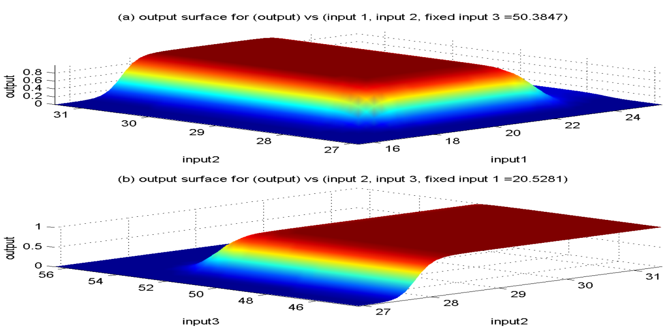

Fig. 2. ANFIS1 inputs-output mapping surface, (a) input 3 is fixed to be 50.387; (b) input 1 is fixed to be 20.5281.

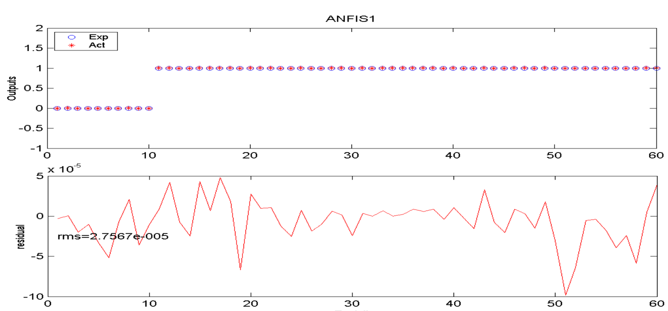

Fig. 3. ANFIS1 testing results and the corresponding error curves.

To study the effect of noise on the proposed ANFIS-2DWT method, random Gaussian white noise is added to the response of these 120 test cases. The noise intensity is defined by the signal-to-noise ratio (SNR):

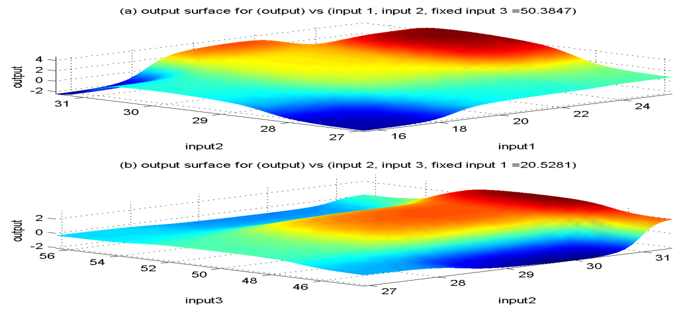

Fig. 4. ANFIS2 inputs-output mapping surface, (a) input 3 is fixed to be 50.387; (b) input 1 is fixed to be 20.5281.

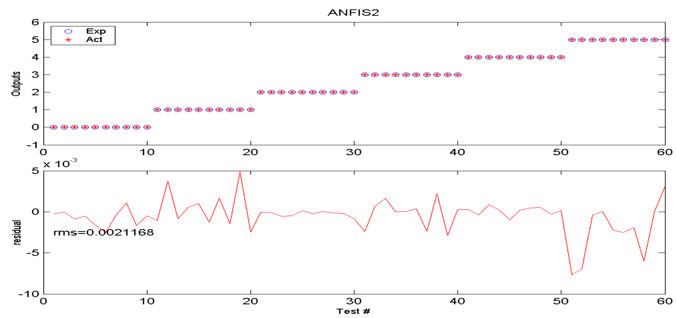

Fig. 5. ANFIS2 testing results and the corresponding error curves.

$$SNR(dB) = 20\log_{10}\frac{A_{signal}}{A_{noise}} \qquad (12)$$

where A_{signal} and A_{noise} refer to the root mean square (rms) amplitude of signal and noise, respectively. Fig. 6 ~ Fig. 8 show the testing results of ANFIS1 (level 1 damage assessment) with SNR=20,10,5, respectively. The ratios of the rms values between the noise and the signal for these three cases are 10%, 31.6% and 56.2%, respectively. It is seen that by using ANFIS-2DWT method, the damage can be correctly detected when SNR is no smaller than 10 dB. Fig. 9 ~ Fig. 11 show the testing results of ANFIS2 (level 2 damage assessment) at these noise levels. It can be seen that ANFIS2 can locate damage even when SNR=10dB. These results suggest that measurement noise does not seem to affect the proposed method for these two levels of damage assessment. This property can be attributed to the 2D WT: the effect of noise can be alleviated by choosing sub-signals less affected by noise.

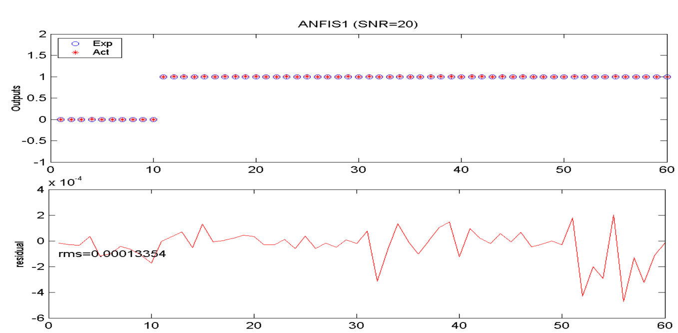

Fig. 6. ANFIS1 testing results and the corresponding error curves, SNR=20.

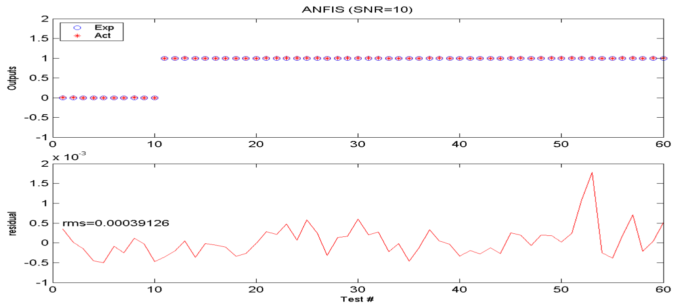

Fig. 7. ANFIS1 testing results and the corresponding error curves, SNR=10.

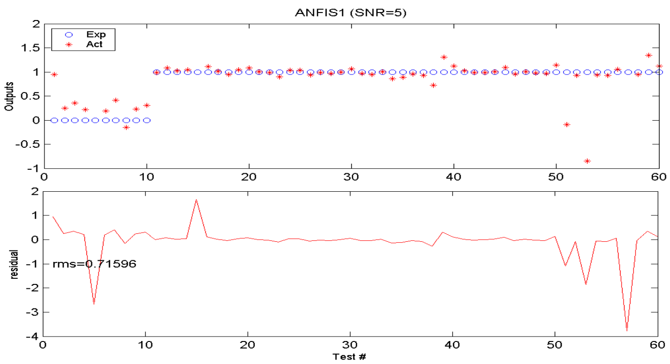

Fig. 8. ANFIS1 testing results and the corresponding error curves, SNR=5.

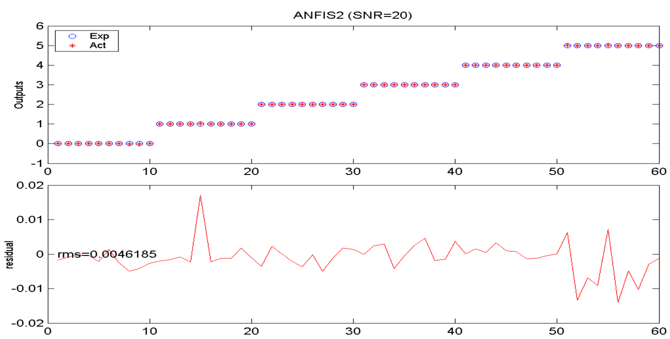

Fig. 9. ANFIS2 testing results and the corresponding error curves, SNR=20.

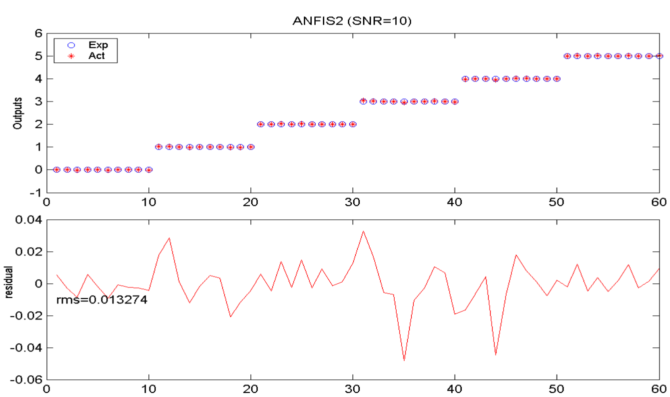

Fig. 10. ANFIS2 testing results and the corresponding error curves, SNR=10.

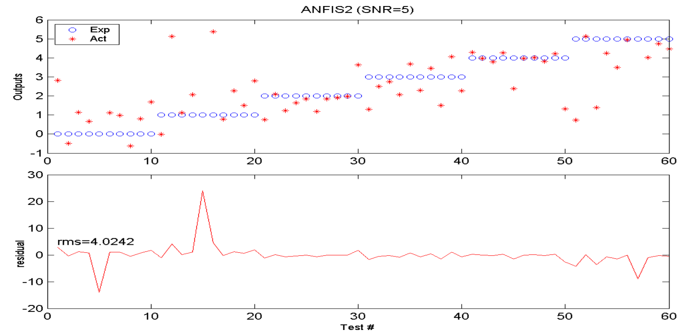

Fig. 11. ANFIS2 testing results and the corresponding error curves, SNR=5.

V. Conclusion

In this paper, an approach to structural damage detection combining ANFIS for damage classification and 2D WT for sensor fusion and feature extraction has been introduced. The structural vibration response signal is decomposed by the 2D WT into a number of sub-signals (images), from which some are selected based on their energy percentages. The energy percentages of the selected signals are taken as inputs to the ANFIS model. The output of the ANFIS is a condition index, which can be a Boolean value (0 or 1) for level 1 damage assessment use, or a number of values for level 2 damage assessment use. Provided an ANFIS model is well-trained by the available data, it can be used for health monitoring and damage localisation. The proposed method has been applied to the data from a cantilever beam for damage detection and localisation. The testing result shows that the method is successful in detecting and localising damage even in the presence of noise. Therefore, the proposed damage assessment methodology of combining ANFIS with 2D WT has great potential in structural health monitoring systems (monitoring systems which are able to interrogate sensor measurements autonomously for indications of structural damage).

References

[1] H. Sohn, C.R. Farrar, F.M. Hemez, D.D. Shunk, D.W. Stinemates, and B.R. Nadler, "A review of structural health monitoring literature: 1996-2001," Los Alamos National Laboratory Report LA-13976-MS, 2003.

[2] C.R. Farrar, W. Doebling and D.A. Nix, "Vibration-based structural damage identification," *Phil. Trans. R. Soc. Lond. A.*, vol. 359, pp. 131-146, 2001.

[3] S. Mallat, *A wavelet tour of signal processing*, San Diego: Academic Press, 1998.

[4] G.G. Yen and K.C. Lin, "Wavelet packet feature extraction for vibration monitoring," *IEEE Trans. on Industrial Electronics*, vol. 47, no. 3, pp. 650–667, 2000.

[5] Z. Sun and C.C. Chang, "Structural damage assessment based on wavelet packet transform," *Journal of Structural Engineering*, vol. 128, pp. 1354-1361, 2002.

[6] Z. Sun and C.C. Chang, "A statistical wavelet-based method for structural health monitoring," *Journal of Structural Engineering*, ASCE, vol. 130, no. 7, pp. 1055-1062, 2004.

[7] S.T. Quek, Q. Wang, L. Zhang and K.-K. Ang, "Sensitivity analysis of crack detection in beams by wavelet technique," *International Journal of Mechanical Sciences*, vol. 43, no. 12, pp. 2899–2910, 2001.

[8] J.S. Walker, *A primer on wavelets and their scientific applications*, New York: Chapman & Hall/CRC, 1999.

[9] J.-S.R. Jang, C.-T. Sun, E. Mizutani, *Neuro-fuzzy and soft computing: A computational approach to learning and machine intelligence*, NJ: Prentice Hall, 1997.