Smart Structures and Systems, *Vol. 12, No. 3-4 (2013) 327-344*
DOI:http://dx.doi.org/10.12989/sss.2013.12.3_4.327

Theoretical and experimental study on damage detection for beam string structure

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(Received July 20, 2012, Revised October 7, 2012, Accepted October 27, 2012)

Abstract. Beam string structure (BSS) is introduced as a new type of hybrid prestressed string structures. The composition and mechanics features of BSS are discussed. The main principles of wavelet packet transform (WPT), principal component analysis (PCA) and support vector machine (SVM) have been reviewed. WPT is applied to the structural response signals, and feature vectors are obtained by feature extraction and PCA. The feature vectors are used for training and classification as the inputs of the support vector machine. The method is used to a single one-way arched beam string structure for damage detection. The cable prestress loss and web members damage experiment for a beam string structure is carried through. Different prestressing forces are applied on the cable to simulate cable prestress loss, the prestressing forces are calculated by the frequencies which are solved by Fourier transform or wavelet transform under impulse excitation. Test results verify this method is accurate and convenient. The damage cases of web members on the beam are tested to validate the efficiency of the method presented in this study. Wavelet packet decomposition is applied to the structural response signals under ambient vibration, feature vectors are obtained by feature extraction method. The feature vectors are used for training and classification as the inputs of the support vector machine. The structural damage position and degree can be identified and classified, and the test result is highly accurate especially combined with principle component analysis.

Keywords: beam string structure; damage detection; wavelet packet decomposition; support vector machine; principle component analysis

1. Introduction

Space structures, such as space trusses and latticed shells, are three-dimensional representations of equilibrium equations and symbols of structural design, simulation and construction in civil engineering. Space structures are widely used for many advantages such as large stiffness, light mass and low cost, and the structural styles are also novel and prolific. As other building structures, space structures are inevitable to subject to environmental corrosion, long term fatigue effects or natural disasters, and then the damage accumulates during long service period. Furthermore, many large space structures are constructed as important building such as gymnasium, exhibition hall and station hall, etc. Therefore, it is necessary to detect the potential damage accurately and promptly in order to assure structural capacity and safety. Under this background, intelligent heath monitoring and damage detection for structures become an important technology.

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http://www.techno-press.org/?journal=sss&subpage=8 ISSN: 1738-1584 (Print), 1738-1991 (Online)

The damage detection is realized by placing various sensors which collect signals and analyzing the data with detection algorithms in the computers at the terminal. Because the service environment is complicated and the degrees of freedom of large and complex structures are excessive, there are no perfect damage detection methods for space structures. As a new type of space structure, beam string structures (BSS) are made by combining tension members with such rigid members as flat arches, beams and struts. Beam string structures are applied in large buildings gradually for having better stiffness and stability and light weight. Hence, it is important to improve the method for detecting the damage patterns and locations on beam string structures with less sensors and more accurate algorithms.

In this study, wavelet packet decomposition is applied to the structural response signals under ambient vibration and the feature vectors such as energy of wavelet frequency bands are obtained by feature extraction method. After principal component analysis (PCA), the feature vectors are used to establish SVMs and classify different damage patterns. Hence, a new structural damage detection method is presented. This method is applied to a single one-way arched beam string structure for damage detection and the results demonstrated that this method is accurate.

2. Beam string structures

As a new type of hybrid prestressed string structures and a typical self-balancing space system, beam string structure is composed by lower string cables, struts, compressive and bending members and vertical connecting members (Saitoh and Okada 1999). By combining the advantages of high bending stiffness of rigid members and strong tensile strength of flexible members, beam string structure can be made with long spans for its strong stiffness, stability and light weight. In general, a single beam string structure behaves as a system with plane stress state though the section of beam, arch and truss, while the combination of multiple beam string structures form a spatial stress state structure.

The strings are the most important members in the BBS system. The effects of strings are as follows:(1) formation of a balanced system and supplying global stabilization; (2) bracing effects; (3) stress control of bending or compressive members; (4) control of displacement and frames shape; (5) enhancing geometrical stiffness.

The prestress is introduced to the string with optimum amount in order to realize the functions as follows: (1) additional performance in resistance for compressive force of strings. (2) security of straightness for strings. (3) additional stiffness, especially geometrical stiffness. (4) elimination of initial stretch of strings. (5) decrease in the stress of bending members and compressive members. (6) control of deformation and the shape of frames.

Beam string structures are applied in several gymnasiums such as Green Dome Maebashi, Ogasayama Dome and Urayasu Municipal Sports Hall in Japan, and BBS is also used in the terminal building of Shanghai Pudong aerodrome and Guangzhou international exhibition center in China. Because beam string structure is a partial flexible structure with strong responses under dynamic excitations, the seismic responses and effects under wind load are the dominating factors for structural design (Wu 2008, Xue 2009). The prestress loss of steel string on the BSS will occur under strong dynamic effect, and the compressive and bending members and vertical connecting members will be damaged also. It is important to monitor the performance of the prestress on the string and other major members in order to protect the total mechanical property. Hence, it is necessary to detect the damage status in order to assure the safety, durability and applicability of BSS.

3. Reviews on damage detection methods

Intelligent heath monitoring and damage diagnosis for structures become an important technology to study (Housner 1997), detecting and predicting the structural damage in time is necessary for future engineering. Detecting structural damage state by its dynamic characteristics, such as frequencies, modal shapes and frequency-domain transfer function is an important method of structural damage detection. However, these damage detection methods based on vibration testing have respective limitation (Yan and Cheng 2007).

For slight damage, damage detection by frequency or modal shape changes directly is nearly infeasible (Yuen *et al*. 1985, Rizos *et al*. 1990, Salawu *et al*. 1997). Curvature modal analysis needs adequate measuring points to ensure the accuracy (Sampaio 1999). Flexibility matrix method is hard to reflect structural local damages (Pandey and Biswas 1994). Modal strain energy method can obtain different results using different test modals (Yao *et al*. 1992).

Structural health monitoring (SHM) is a multidisciplinary and integrated technology; hence it is difficult to resolve many practical problems for large and complex structures based on vibration testing merely. Improving the finite element updating technology for health monitoring and state evaluation, combing modern signal analysis technology and soft computing theory, mining structural characteristic data deeply, realizing the real-time, online dynamic monitoring and control, is the developmental direction for SHM.

Recently, many advanced technology and intelligent methods, such as digital filter technology, wavelet transform (WT) analysis (Wang 1999, Moyo 2002, Sun 2003, Hera 2004, Li 2009a,b, Yi 2011, Yi 2012), artificial neural networks (ANNs) (Teboub 1990, Wu 1992) and genetic algorithm (GA), are studied to detect the structural global and local damage information, and to optimize the SHM system.

Wavelet packet transform (WPT) is a new method of signal processing that has recently been applied to various science and engineering with great success (Yi 2013). The specific local properties of wavelet packet can be particularly useful to describe signals with sharp spikes or discontinuities. It is effective for the structural damage signals process by wavelet packet because its multi resolution analysis capability and time-frequency localization (Peng 2012). As an effective time-frequency tool, wavelet could detect whether damage has occurred but it is not effective to detect different damage states. Intelligent tools are needed to solve the damage classification problem, which includes damage location and degree.

Artificial neural networks (ANNs) have been applied in structural damage detection as generalization or classification problems based on learning pattern from examples or empirical data model (Amaravadi 2002). The ANN method for structural damage detection has some advantages such as strong self-adaptive and fault-tolerant capabilities, and it has been approved to be effective for some elements and simple structures (Fang 2005). However, the traditional neural networks suffers from a number of weaknesses, including the need for a large number of controlling parameters, difficulty in obtaining a stable solution and the danger of over-fitting.

Compared to traditional feed-forward ANN, Support vector machines (SVMs) (Vapnik 1995) do not have some problems such as local minimization, the number selection of nodes in hidden layer and the dimension disaster. SVM, which based on statistical learning theory, are gaining applications in the areas of machine learning, data classification and pattern recognition because of the high accuracy and good generalization capability (Cristianini 2000. Samanta 2003, Yao 2012).

4. Wavelet packet decomposition

The wavelet transform is devised to maintain both the time and frequency properties of a signal. This analysis is based on a complete set of localized functions (named wavelets) that span both the time and frequency domains. The WT of *f(t)* is thus a function of two parameters *a* and *b*, where *a* represents a frequency scale, and *b* indicates the time location of the wavelet

$$W_f(a,b)=\int_{-\infty}^{\infty} f(t)\psi_{a,b}(t)dt=\int_{-\infty}^{\infty} f(t)\frac{1}{\sqrt{a}}\psi(\frac{t-b}{a})\ dt \tag{1}$$

where *f(t)* is measured over a finite time interval *T*. $\psi(t)$ is called the mother wavelet and $\psi_{a,b}(t)$ is a scaled and translated wavelet. Unlike the Fourier transform, there are numerous mother wavelets, and $\psi(t)$ is chosen according to the problem.

WT can also be viewed as a discrete set of filters. Generally, an exact quadrature mirror filter $h(k)$ is defined as

$$\sum_k h(k-2j)h(k-2j)=\delta_{i,j} \qquad \sum_k h(k)=\sqrt{2} \tag{2}$$

In multi-resolution analysis, the orthonormal scaling function $\phi(t)$ and wavelet function $\psi(t)$ satisfy the dyadic scaling equation

$$\phi(t)=\sqrt{2}\sum_k h(k)\phi(2t\text{-}k) \tag{3}$$

$$\psi(t)=\sqrt{2}\sum_k h(k)\psi(2t\text{-}k) \tag{4}$$

where $g(k)=(-1)^k h(1+k)$. Let $w_0=\phi(t)$ and $w_1=\psi(t)$, the above dyadic scaling equations can be expressed as the following recursive equations

$$w_{2n}(t)=\sqrt{2}\sum_k h(k)w_n(2t-k) \tag{5}$$

$$w_{2n+1}(t)=\sqrt{2}\sum_k g(k)w_n(2t\text{-}k) \tag{6}$$

Then, the functions $\{w_n(t)\}$ form an orthonormal basis and are called the orthonormal wavelet packets of function $\phi(t)$ .If the operations for decomposition of multi-analysis are defined as

$$H[s_k](i)=2\sum_k s_k h(k-2i) \tag{7}$$

$$G\left[s_k\right](i)=2\sum_k s_k g(k-2i) \tag{8}$$

Thus, we have

$$w_n(t-l)=\sqrt{2}\sum_k h(l-2k)w_{2n}(\frac{t}{2}-k)+g(l-2k)w_{2n+1}(\frac{t}{2}-k) \tag{9}$$

If a signal *f(t)* satisfies

$$f(t)=\sum_k s_k^j w_n(2^{-j-1}-k) \tag{10}$$

its *j*-layer binary decomposition in the basis of orthonormal wavelet packets can be deduced as

$$f(t)=\sqrt{2}\sum_i H\left[s_k^j\right](i)w_{2n}(2^{-j-1}-i)+\sqrt{2}\sum_i G\left[s_k^j\right](i)w_{2n+1}(2^{-j-1}-i) \tag{11}$$

By wavelet packet decomposition, any signal can be decomposed into two parts, i.e., the project on $\left\{w_{2n}(2^{-j-1}-1)\right\}$ operated by H and that on $\left\{w_{2n+1}(2^{-j-1}-1)\right\}$ operated by G clearly. Wavelet packet decomposition of a signal has better localization effect than that of wavelet. Therefore, it used to adaptively choose the corresponding frequency bandwidth according to the characteristics of the detection signal and to enhance the resolution both in frequency and time domains for damage detection.

5. Signals feature extraction and reduction

As the differences of signals between original and damaged structures are generally insignificant in the early stage of damage, extraction of damage index directly from the measured form of signal (even decomposed by wavelet packets) is still difficult. Therefore, the energy spectrum analysis is used to enhance the sensitivity of damage features.

The second order norm of an original signal *f(t)* is

$$\| f\|_2^2=\int_R \left| f(x)\right|^2 dx \tag{12}$$

Then, it is the equivalent energy of the original signal in time domain. For allowable wavelet ψ, we have

$$\iint_R \left|W_\phi f(a,b)/a\right|^2 dbda=\| f\|_2^2 \tag{13}$$

Thus, there is an equivalent relationship between the energy of wavelet transform and that of the original signal. Therefore, it is reliable to express energy variation in the original signal by energy spectrum of the response signal decomposed by wavelet packets. Hence, in the energy spectrum of wavelet packets, the sum of square of the decomposed signal is selected as the energy feature within every subspace (frequency span). In subspace $V_{2^j i}$, i.e., the *i*th frequency span of the *j*th layer, the result of wavelet packet decomposition is expressed by $\{S_i(k), k = 1,2,...,M\}$, and its energy is expressed by

$$E_{2^j i} = \sum_{k=1}^{M} |S_i(k)|^2 \tag{14}$$

where *M* is the length of samples in the subspace.

In the processes of structural health monitoring, the structural response signals, such as acceleration, strain and stress, vary when a structure suffers different damage including grade and location, and the vibration energy of elements be heightened or be reduced. Hence, the coefficients in some frequency bands are different for structural joint signals, and the energy in the frequency bands can be extracted as feature vectors to detect damage. The proposed procedure for feature extraction consists of four steps:

Step1: Calculate the wavelet packet transform of a set of signals. The acceleration or strain signals are collected by the sensors on the structural joints. Apply wavelet packet transform to the signal, and the result of wavelet packet decomposition in the *N*th layer is S_{NJ}, $j = 1,2,\cdots, 2^N$, and the frequency band number is 2^N.

Step2: Reconstruct wavelet packets and calculate the energy of all the frequency bands. The energy of the reconstruct signals S_{Nj} is $E_{Nj} = \int |E_{Nj}(t)|^2 dt = \sum_{k=1}^{n} |x_{jk}|^2$, where, x_{jk} is the amplitude of the kth discrete point and *n* is the number of the discrete points. The modulus of S_{Nj} is $N_{Nj} = (E_{NJ})^{1/2}$.

Step3: Construct feature vectors. The modulus of S_{Nj} in all the frequency bands can be calculated and a sequence can be obtained as $\{N_{Nj},\ j = 1, 2, \cdots, 2^N\}$. Therefore, a feature vector corresponding to the energy can be constructed as $p = (N_{N1},\ N_{N2},\ \cdots,\ N_{N2^N})$.

After the feature vectors are extracted, data compression technique such as principal component analysis (PCA) is recommended to reduce the dimensions and amplify the diversity. Principal component analysis is a statistical technique that linearly transforms an original set of variables into a substantially smaller set of uncorrelated variables that represents most of the information in the original set of variables (Joliffe 1986). It can be viewed as a classical method of multivariate statistical analysis for achieving a dimension reduction. Because of the fact that a small set of uncorrelated variables is much easier to understand and use in further analysis than a larger set of correlated variables, this data compression technique has been widely applied.

6. Review on support vector machine

As a novel network algorithm, support vector machine (SVM), has developed to a powerful tool for data analysis. It is powerful for the problem with small sampling, nonlinear and high dimension.

In the two-dimensional case, the SVM action can be illustrated in Fig. 1. A series of points for two different classes of data are shown, circles (*class A*) and squares (*class B*). The SVM attempts to place a linear boundary (solid line) between the two different classes and orients this line in such a way that the margin (space between dotted lines) is maximized. The nearest data points used to define the margin are known as support vectors (gray circles and square). Support vectors, not the number of input features, contain all of the information needed to define the classifier. One remarkable property of SVM is its ability to learn can be independent of the feature space dimensionality. This means that SVM can generalize well in the presence of many features.

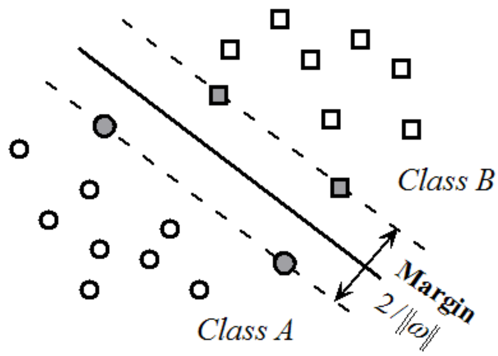

Fig. 1 Separation of two classes by SVM

Given a set of training data

$$D=\{(\mathbf{x}_1,y_1),\ldots,(\mathbf{x}_i,y_i),\ldots,(\mathbf{x}_n,y_n)\},\quad \mathbf{x}\in\mathrm{R}^n,\ y\in\{-1,\ 1\} \tag{19}$$

where $\mathbf{x}_i$ is the training data, n is the number of training data and y_i is the class label (1 or−1) for $\mathbf{x}_i$.

Firstly, a nonlinear function is employed to map the original input space R^n to N-dimensional feature space.

$$\varphi(\mathbf{x})=(\varphi_1(\mathbf{x}),\varphi_2(\mathbf{x}),\ldots,\varphi_N(\mathbf{x})) \tag{20}$$

Then the separating hyper plane is constructed in this high dimension feature space. The classifier takes the form as

$$\mathrm{y}(\mathbf{x})=\mathrm{sgn}\,(\mathbf{w}\cdot\varphi(\mathbf{x})+b) \tag{21}$$

where **w** is the weight vector and b is a scalar.

To obtain the optimal classifier, || **w** || should be minimized under the following constraints

$$y_i[\mathbf{w}\cdot\varphi(\mathbf{x})+b]\geq 1-\xi_i,\quad i=1,2,\ldots,n \tag{22}$$

The variables ξ_i are positive slack variables, which is necessary to allow misclassification. Thus, according to principle of structural risk minimization, the optimal problem can be formulated as minimization of the following objective function J

$$\begin{aligned} &\text{minmize} \quad J(\mathbf{w},\xi)=\frac{1}{2}\|\mathbf{w}\|^2+C\sum_{i=1}^{n}\xi_i \\ &\text{subject to} \quad y_i[\mathbf{w}\cdot\varphi(\mathbf{x})+b]\geq 1-\xi_i, \quad \xi_i\geq 0, \quad i=1,2,\ldots,n \end{aligned} \tag{23}$$

where C is the margin parameter.

According to Lagrangian principle, the above problem can be transformed to its corresponding form as follows

$$\begin{aligned} &\text{maximize} \quad W(a)=-\frac{1}{2}\sum_{i,j=1}^{n}a_i a_j y_i y_j(\varphi(\mathbf{x}_i),\varphi(\mathbf{x}_j))+\sum_{i=1}^{n}a_i \\ &\text{subject to} \quad \sum_{i=1}^{n}a_i y_i=0, \quad 0\leq a_i\leq C, \quad i=1,2,\ldots,n \end{aligned} \tag{24}$$

If $a_i > 0$, the corresponding x_i is called support vector. In general, support vectors are only a small part of the training samples. Eq. (24) is a quadratic programming problem constrained in a convex set, and the solution is unique.

Finally, the optimal separating hyperplane is obtained as follows

$$\sum_{\mathrm{SV}}a_i y_i K(\mathbf{x}_i,\mathbf{x})+b=0 \tag{25}$$

where SV are the support vectors. Then the nonlinear classifier is

$$y=\mathrm{sgn}(\sum_{\mathrm{SV}}a_i y_i K(\mathbf{x}_i,\mathbf{x})+b) \tag{26}$$

This distinguishing function is the so-called SVM. From the above analysis, it can be concluded that SVM is decided by training samples and kernel function.

The feature vectors extracted from the signals after PCA can be used as the input vectors of SVMs. SVMs can be applied to structural damage detection and classification as a classifier. A set of training samples are $T=\{(\mathbf{x}_1,y_1),\ldots,(\mathbf{x}_i,y_i),\ldots,(\mathbf{x}_n,y_n)\}$, $\mathbf{x}\in\mathrm{R}^n$, $y\in\{-1,\ 1\}$, where $\mathbf{x}_i$ is the input vectors, y_i is the expectation value, n is the number of training data. Assume the number of support vectors is N in all the input and they are SV_1 , SV_2 , ... , SV_N respectively.

According to SVM algorithm and mechanism, the classification training process end when the classification results satisfy the demand. The basic SVM algorithm is about two-class problem. For multi-class problem, one of the classic algorithms is Improved Sequential Minimal Optimization (SMO) and all the classes can be treated by a set of two-value classifiers. The trained SVMs can be used as an effective tool for structural damage detection.

7. Damage detection test on beam string structure

In this paper, the dynamic test and damage detection for a single one-way arched beam string structure is presented. The experimental model is constructed with the scaling factor of 1/15. The original model is an arched beam string structure as shown in Fig. 2. The span of upper arch l is 3 m. The radius vector f of the upper arch and the sag of the lower chord are both 0.5 m. If the horizontal and vertical coordinate of the arch and the cable is x and y respectively, the parabolic equation of arch axis is $y=4fx(3-x)/l^2$ under uniformly distributed loads along whole span. The upper arch is a reversed triangular truss, the width is 200mm and the height is 150 mm. The external diameter of the upper chords is 32 mm and the thickness is 2.5 mm. The corresponding dimension of the lower chords is 32 mm and 2.5 mm, and 18 mm and 1.2 mm for the web members. The external diameter of the struts is 32 mm and the thickness is 2.5 mm. The diameter of the cable is 10 mm. According to the service load, two counter weight blocks with the total weight of 30 kg are fixed on each board of the upper joints. Because the thrust on the end of arch is resisted by the cable but not the supports and the beam string structure is a self-balancing system, the supports are composed of one hinged bearing and one slideable elastic bearing.

Fig. 2 Side view of BSS model

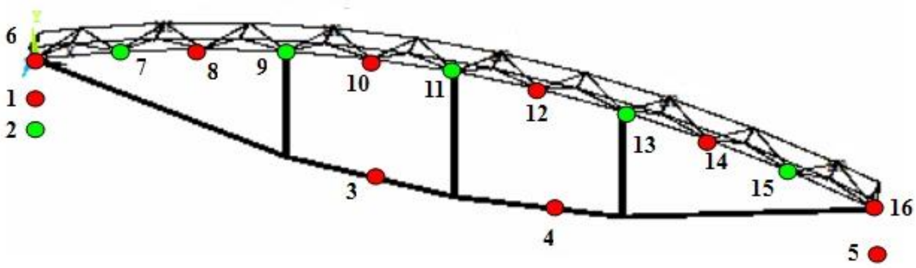

Fig. 3 Scheme of accelerometers placement (red for vertical and green for horizontal)

Fig. 4 Force sensor on the tension side of the cable

For the dynamic damage detection test on beam string structure, 16 accelerometers were installed. Among them, 11 sensors were fixed on the lower chord joints of the arch truss in the horizontal and vertical direction alternatively, and two sensors were placed on the two middle spans of the cable. Two sensors in horizontal and vertical respectively were fixed on the hinged bearing and one vertical sensor was on the slideable bearing. The arrangement and numbering plan is shown in Fig. 3. A force sensor is installed near the tensioning end on the cable, as shown in Fig. 4.

7.1 Prestress identification

Cables are the most critical structural components in beam string structures. The tension force in the cable controls the internal force distribution. Therefore, the cable tension force is an important index in the damage detection and long-term health monitoring. A dynamic and a static data acquisition system were used respectively to collect and analyze the signals of acceleration and strain. In order to simulate the different cases of prestress loss, six types of prestress were applied to the cable from the slack state step by step, and the prestress value is adjusted by controlling the strain value on the force sensor. The strain and prestress values from the force sensor directly are shown in Table 1.

In each of six cases, the two middle spans of the cable were knocked on respectively, as shown in Fig. 5 and the acceleration signals were analyzed by Fast Fourier transformation.

Ignoring the effect of the sag and flexural rigidity, the simplest relationship to calculate the cable forces based on the vibration frequency is the so-called "taut string" chord equation

$$T = \frac{4\rho l^2 f_n^2}{n^2} \tag{27}$$

where T is cable tension; ρ is cable mass per unit length; l is length between cable fixed ends; and f_n is n^{th} natural frequency. The fundamental frequencies of the cable in different cases are computed and the cable tensions are calculated according to conventional formulas, the results are compared with the measured tensions.

Fig. 5 The accelerometer on the cable

The actual mass per unit length of the cable is 0.338 kg/m and the length of the middle span is 1.2 m. The measured fundamental frequencies and the calculated tensions are listed in Table1. The total mass of the accelerometer and the binding material is 0.123 kg, and the influence of sensor could not be ignored for this scale model, and it is converted into linear density and the modified cable mass per unit length is 0.420 kg/m.

The modified cable tensions are list in Table 1 also, and it can be found that the values are similar to the measured values, as shown in Fig. 6. The method based on frequencies is simple and accurate, while the installation of force sensor need to cut off the cable first and the safety of the cable have been reduced artificially. Hence, the cable tension could be calculated from accelerometers in stead of placing force sensors in long-term monitoring of cable, and the excitations can be ambient vibration or instantaneous electronic impulse from micro device on the sensors.

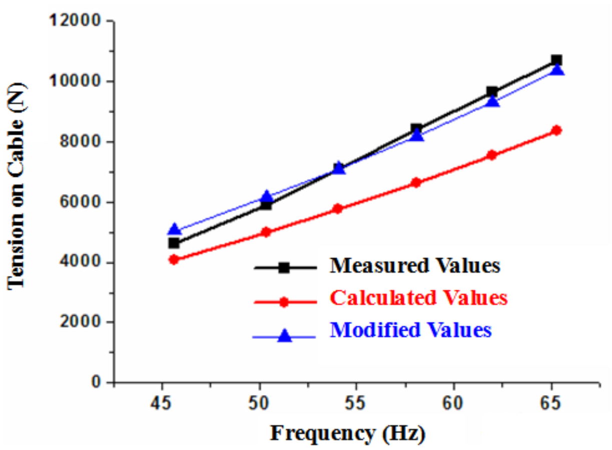

Fig. 6 Computed cable force and test value

Table 1 Strain and tension of cable

Prestress Cases	Strain	Measured Tension (N)	Fundamental Frequencies (Hz)	Calculated Tension (N)	Modified Tension (N)
1	473.11	4636.43	45.62	4090.11	5052.48
2	602.69	5906.36	50.38	4987.29	6160.76
3	722.49	7080.44	54.08	5746.74	7098.91
4	860.64	8434.23	58.10	6631.94	8192.39
5	985.33	9656.24	61.99	7550.04	9326.52
6	1092.9	10710.51	65.32	8383.79	10356.44

The monitoring of the prestress loss on the cable could also be realized by energy spectrum from wavelet packet. A group of acceleration signals is collected under ambient vibration, and the sampling time lasts 300 seconds for each state and the sampling frequency is 2000. The signals are decomposed by three-level wavelet packet, and the wavelet type belongs to Daubechies series.

Each sample signal is transformed into a set of normalized eight-dimension energy vectors as shown in Fig. 7. In the figure, the abscissa is frequency bands and the ordinate is normalized energy vector, the subgraphs (1)-(6) represent the case 6 to case 1respectively. It can be seen that the energy of frequency bands concentrate to low frequency and the natural frequencies descend gradually along with the loss of prestress. Hence the damage on cable can be detected, but the sampling time is longer and the tension values can not be calculated accurately.

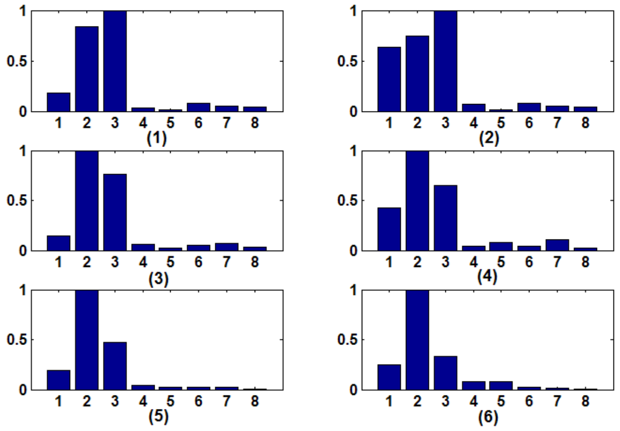

Fig. 7 Frequency band energy from wavelet packet decomposition

7.2 Damage detection for web members

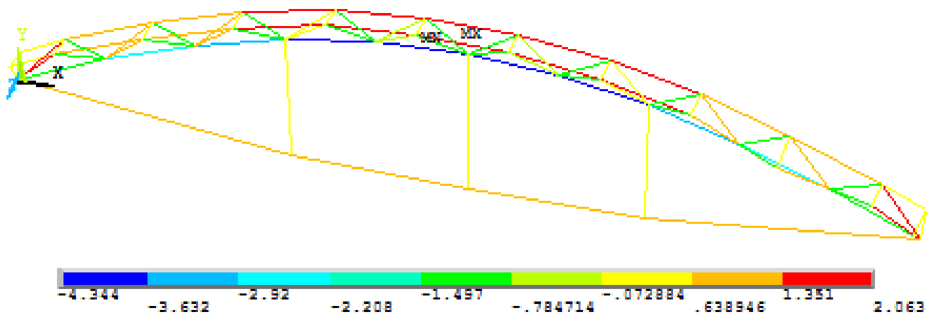

Fig. 8 Cloud picture of distributed axial force on BBS (Unit: 10^6 N/m^2)

The cable tension value is 10711 N when the prestress loss test ended. The positive bending moment is equal to the negative bending moment for the whole beam string structure, and the damage detection test on the arch truss is studied in this state. Where, the positive bending moment means the moment on the upper arch produced by the vertical load alone, and the negative bending moment is the moment which is supplied only by the prestress. The distributed axial force on BSS is analyzed by finite element model, and the stress of the web member near the bearing is maximal besides the stress on the cable, as shown in Fig. 8 and Table 2. The chords on the arch truss and the struts could not be damaged in order to maintain the integrity of BBS, so four web members near the bearing is selected to be cut at one end one by one in order to simulate the failure statuses as shown in Fig. 9. For each damage member, the damage degrees include two cases as 50% and 100%, and parts are shown in Figs. 10 and 11. In general, there are 9 cases which include 8 different damage states and one health state to be detected.

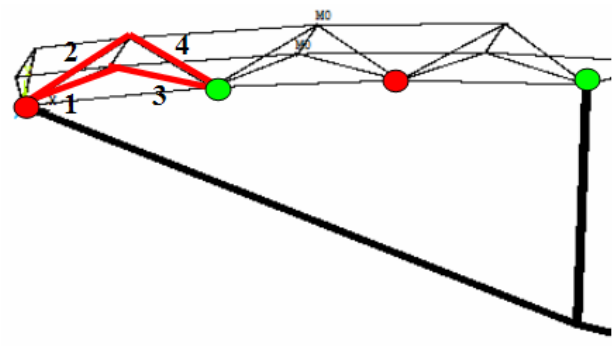

Fig. 9 Damage location of web member

Fig. 10 100% damage of one end of web member 1

The acceleration signals of all the sensors on the BBS are collected under ambient vibration in order to verify the detection method of wavelet packet and support vector machine. Ten groups of signals are collected totally and each lasts 60 seconds and the sampling frequency is 2000. To enhance the actual analysis efficiency, only the signals from four sensors marked 13-16 in Fig. 3 are decomposed considering they are most sensitive to the damage locations and degrees.

Fig. 11 100% damage of four web members

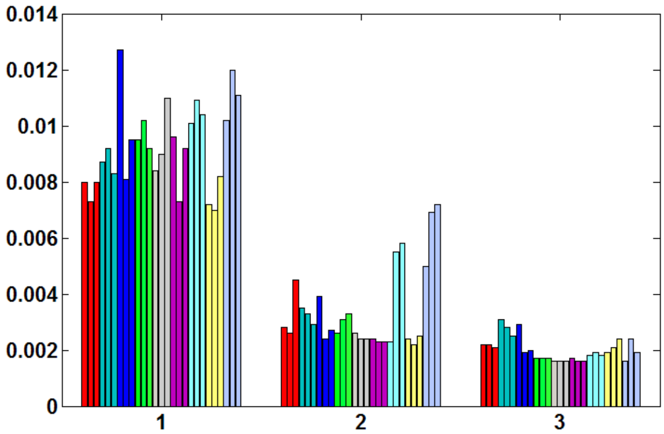

Fig. 12 Energy of 1st-3rd Frequency bands

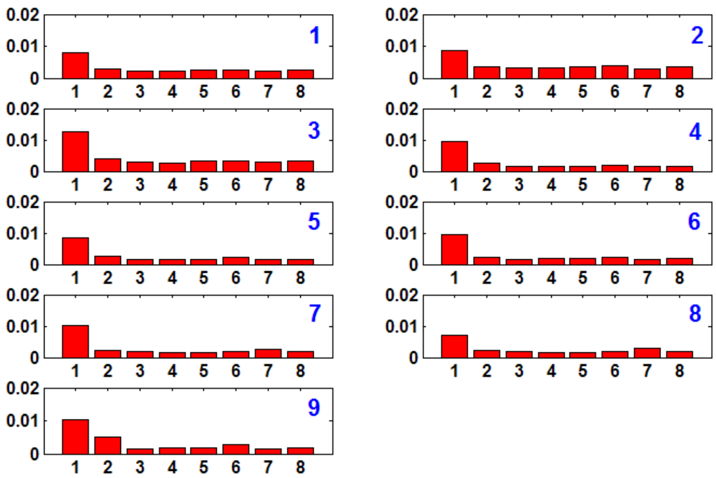

Fig. 13 Frequency bands energy of Sensor 1

The signals are decomposed by three-level wavelet packet which belongs to Daubechies series. The first three energy vectors of three groups of signals selected with random are shown in Fig. 12 with the example of sensor 15, and the abscissa is frequency bands and the ordinate is energy vectors. In the figure, the columns have the same color represent the energy vectors in the same damage cases. It can be seen that the vectors in the same case are close and can be obviously distinguished from other cases.

All the energy vectors under different damage cases from sensor 15 are shown in Fig. 13. In the figure, the subgraphs (1)-(9) represent the cases which are from being intact to all the four web members are damage totally respectively.

Table 2 Illustration of distributed axial force

Location	Mechanical Behavior	Stress Distribution
Upper Chords	under compression	Maximum in middle spans
Lower Chords	under compression	Maximum in middle spans
Web Members	under compression besides tension mostly near supports	Maximum tension near supports maximum compression in middle spans
Struts	under compression	
Cable	under maximum tension	
Support Vertical Members	less stress	

Table 3 Results of the classification by SVM method

Actual Cases / **Results**	1	2	3	4	5	6	7	8	9	1	2	3	4	5	6	7	8	9	**Accuracy**
SVM1	1	2	3	4	4	6	5	3	9	1	2	3	4	3	6	5	8	9	66.7%
SVM2	3	2	3	4	3	6	8	8	2	1	2	3	4	4	6	7	8	9	61.1%
SVM3	1	2	3	4	4	6	7	8	2	1	2	3	4	3	6	7	8	9	61.1%
SVM4	6	5	3	4	4	6	5	8	8	1	2	3	4	4	6	5	8	9	50.0%
Integrated	1	2	3	4	4	6	5	8	2	1	2	3	4	4	6	7	8	9	66.7%

For each accelerometer, six groups of signal are selected as the training samples for the support vector machine and other four groups are test samples. The test samples are classified after the support vector machine has been established, and the results are listed in Table 3. In the table, SVM1-SVM4 indicates the support vector machine established according to the signals from sensors 16-13 respectively, and the damage cases indicates the cases from heath to the state that all the four web members damaged completely. The false results are marked with rectangular frames and the final integrated result is defined as the result that has most proportions in the four results.

The final correct classifying rate is 66.7%. The method above is feasible but need to be improved in view of some false results are close to the actual cases.

Each group of the original energy vector discomposed from wavelet packet is transformed based on principal component analysis. The accumulation variance percentage is over 92% for the first four principal components so they are chose as the efficient vectors. These four vectors of three groups of signals selected with random are shown in Fig. 14 with the example of sensor 15.

After PCA, all the energy vectors under different damage cases from sensor 15 are shown in Fig. 15. In the figure, the subgraphs (1)-(9) represent the cases which are from being intact to all the four web members are damage totally respectively.

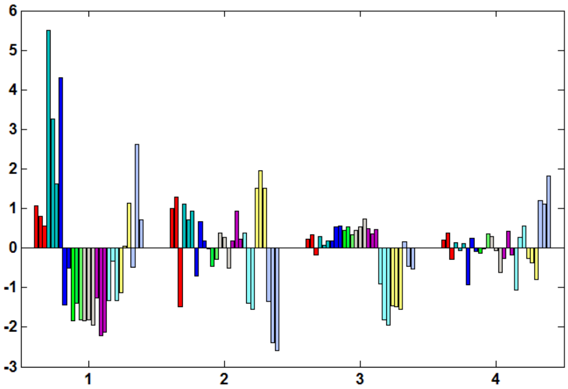

Fig. 14 Energy of Frequency bands by PCA

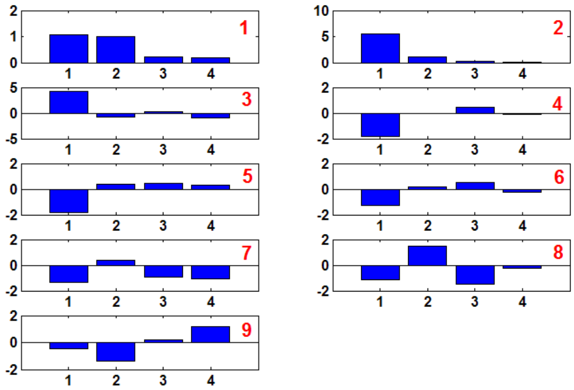

Fig. 15 Damage vectors of Sensor 15 by PCA

Table 4 Results of the classification by SVM method after PCA

Actual Cases / **Results**	1	2	3	4	5	6	7	8	9	1	2	3	4	5	6	7	8	9	**Accuracy**
SVM1	1	2	3	4	3	6	5	8	9	1	2	3	4	5	6	7	8	9	88.9%
SVM2	1	2	3	4	4	6	7	8	9	1	2	3	4	3	6	7	8	9	88.9%
SVM3	1	2	3	4	3	6	7	8	9	1	2	3	4	6	6	6	8	2	77.8%
SVM4	1	2	3	4	4	6	5	8	9	1	2	3	4	4	6	5	8	9	77.8%
Integrated	1	2	3	4	4	6	7	8	9	1	2	3	4	6	6	7	8	9	88.9%

The variance of difference components is obvious and new SVMs can be reestablished without other change, partial results are listed in Table 4. The final integrated correct classifying rate is

88.9%. Hence, the classification and detection method based on PCA and SVM is satisfactory, and the method is proved to be simple, rapid and accurate.

8. Conclusions

In this study, beam string structure (BSS) is introduced as a new type of hybrid prestressed string structures. The composition and mechanics features of BSS are discussed. The main principles of wavelet packet transform (WPT), principal component analysis (PCA) and support vector machine (SVM) have been reviewed. WPT is applied to the structural response signals, and feature vectors are obtained by feature extraction and PCA. The feature vectors are used for training and classification as the inputs of the support vector machine. The method is used to a single one-way arched beam string structure for damage detection. The structural damage location and degree can be detected and classified, and the result is relative accurate. This method has some advantages, such as engineering oriented, low cost and convenient.

However, there are still some important details to be studied. The damage data are only obtained from the experimental results and the fine finite element model is needed and the model modification should be applied in order to get much more date and enlarge the damage classes. For SVM, determining the proper parameters is still a heuristic process, and automation of this process could be beneficial. The maximum possible size of the training set is to be searched. Optimal selection of wavelet basis for different structural styles needs to be addressed in order to assure the accuracy. Some problems such as optimal placement of sensors are also needed additional studies.

Acknowledgments

This work is partially supported by Natural Science Foundation of China under Grant no. 51108009 and 50878010, and Foundation of the Ministry of Education of China for Outstanding Young Teachers in University under Grant no. 20111103120022.

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