Smart Structures and Systems, *Vol. 14, No. 2 (2014) 145-158*
DOI: http://dx.doi.org/10.12989/sss.2014.14.2.145

SVR model reconstruction for the reliability of FBG sensor network based on the CFRP impact monitoring

Xiaoli Zhang[1a], Dakai Liang[*2], Jie Zeng[2b] and Jiyun Lu[2c]

[1]*College of Physics and Electronic Engineering, Xinyang Normal University, 237# Chang'an Road, Xinyang 464000, People's Republic of China*
[2]*The State Key Laboratory of Mechanics and Control of Mechanical Structures, Nanjing University of Aeronautics and Astronautics, 29# Yu Dao Street, Nanjing 210016, People's Republic of China*

(Received July 26, 2012, Revised July 22, 2013, Accepted July 30, 2013)

Abstract. The objective of this study is to improve the survivability and reliability of the FBG sensor network in the structural health monitoring (SHM) system. Therefore, a model reconstruction soft computing recognition algorithm based on support vector regression (SVR) is proposed to achieve the high reliability of the FBG sensor network, and the grid search algorithm is used to optimize the parameters of SVR model. Furthermore, in order to demonstrate the effectiveness of the proposed model reconstruction algorithm, a SHM system based on an eight-point fiber Bragg grating (FBG) sensor network is designed to monitor the foreign-object low velocity impact of a CFRP composite plate. Simultaneously, some sensors data are neglected to simulate different kinds of FBG sensor network failure modes, the predicting results are compared with non-reconstruction for the same failure mode. The comparative results indicate that the performance of the model reconstruction recognition algorithm based on SVR has more excellence than that of non-reconstruction, and the model reconstruction algorithm almost keeps the consistent predicting accuracy when no sensor, one sensor and two sensors are invalid in the FBG sensor network, thus the reliability is improved when there are FBG sensors are invalid in the structural health monitoring system.

Keywords: health monitoring; low velocity impact; fiber bragg grating; support vector regression; sensor network; reliability

1. Introduction

Carbon fiber reinforced polymer (CFRP) composite plate has generated wide interest in the fields of aeronautics and astronautics due to their high strength-to-weight ratio, excellent resistance to corrosion, easy to design (Andres *et al.* 1998). However, the aerospace structure may suffer the fatigue loads and accidental crash in service and produce local damage. In extreme circumstances, the local damage may cause the structure wrecked. Conventional visual and schedule inspection is not only lack of precision, but also the damage can't be found timely. Structural Health Monitoring

*Corresponding author, Professor, E-mail: zxli_nuaa@163.com
[a] Ph. D., E-mail: zxli_nuaa@nuaa.edu.cn
[b] Ph. D., E-mail: zj2007@nuaa.edu.cn
[c] Ph. D., E-mail: lujiyun@nuaa.edu.cn

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

(SHM) consist a system of active and passive sensors and data management, which are able to continuously monitor a structure health status and provide an early warning such as the damage type, position and range etc., thus avoid the severe losses of the structure (Hoschke *et al.* 2008). Various sensors are available for the strain distribution monitoring of composite structure, especially fiber Bragg grating (FBG) sensor offers several advantages over their lightweight, small physical size, high resolution and accuracy, high multiplexing capabilities, corrosion resistance, immune to electromagnetic interference (EMI) etc. (Maaskant *et al.* 1997, Mieloszyk *et al.* 2010). They are ideally suitable for SHM of composite materials such as CFRP.

Various applications such as in SHM for aerospace structures, FBG sensors are mounted on or embedded in the structure with distributed and quasi-distributed network without any serious effect on the structural integrity. Yet surface mounted sensors will be exposed on the outside of the aerospace, they are inevitably affected by sunlight, moisture, erosion and severe mechanical contacts, which make them can't survive for a long time. Furthermore, due to the high degree of multiplexing can reduce in both cost and complexity in a multipoint configuration, multiplexing of more than five FBG sensors is required along a single fiber (Dai *et al.* 2009). This type of network topology has some defects, if fibers, nodes, or sensors link fail, all of the FBG sensor signals behind the failure point will not be demodulated, thus the SHM system may not work as normal. For ensuring safe and efficient operation, SHM system is always used to monitor and control the critical systems and components of the aerospace structure. Therefore, it requires the SHM system must be highly reliable and rugged, ultimately including self-repairing function (Prokopenko *et al.* 2005). Currently, there have been many academic works on the reliability and self-repairing function of SHM system. For example, CSIRO-NASA Ageless Aerospace Vehicle (AAV) concept demonstration Scott *et al.*(2009)proposed a circular segment topology based on optical switch and multi-agent technology to achieve sensor network self-monitoring and self-repairing. Peng *et al.* (2010) proposed optical switches as auxiliary component to check the failure point and reconfigure the FBG sensor network if any link fails in the star-bus-ring architecture, thus the self-healing function of the SHM system is facilitated. Yeh *et al.* (2009) proposed and experimentally investigated a multi-ring passive sensing architecture to enhance the survivability and capacity for the multi-point FBG sensor system.

In this study, with the low velocity impacting loads on the CFRP composite plate as subject, by virtue of the FBG sensor network embedded in the structure, the model reconstruction algorithm which the support vector regression models and parameters are modified dynamically is researched to improve the reliability and survivability of the SHM system when the FBG sensors or fiber nodes are invalid in the network. The idea of this algorithm is performed as follows: if the distance error between the actual value and predicting value is too big to beyond the allowable range, the SHM system should be inspected, especially the FBG sensor network. When certain FBG sensor data display abnormally or can't be achieved by the demodulator, the SVR impacting position predicting model is reconstructed again according to the survival FBG sensors in the SHM system. Then the impacting position identification of the CFRP composite plate is finished by the reconstruction model with the similar predicting precision partly, and it keeps the real-time monitoring of the original sensor network system again. In this way, the reliability and robustness of the SHM system is achieved rather than dismantle the monitored structure to repair the FBG sensor network in the engineering application.

2. Descriptions of support vector regression

Support vector machine (SVM) was developed by Vapnik and his colleagues at AT&T Bell Laboratories in 1995 (Yang *et al.* 2010). SVM is used to describe the classification problem with support vector method firstly, with the introduction of ε-insensitive loss function by Vapnik in 2000, it has been successfully applied to regression problem, and the regression version is named as support vector regression (SVR) (Kapil 2010). In contrast to the traditional regression method, SVR based on the structural risk minimization principle has the excellent abilities of small sample learning and generalization (Guo and Bai 2009).

For the non-linear regression, SVR is a kernel method that performs regression with the kernel function. Considering a training set $\{(x_i, y_i)\}_{i=1}^{n} \subset R^d \times R$, such that x_i and y_i are input variable vector and output variable vector respectively, SVR map any input $x_i \in R^d$ to a higher dimensional feature space H by a nonlinear feature map $\phi(\cdot)$. With this, the linear regression function can be given as $f(x_i) = < w, \phi(x_i) > +b$, where w is a regression coefficient vector in the feature space, $\phi(x_i)$ is a mapping from the input space x_i to the feature space H, b is the model offset and $< \cdot, \cdot >$ is the inner product in feature space (Hu *et al.* 2010).

In terms of the structural risk minimization principle, the coefficient w and b can be obtained from the following function (Ankit *et al.* 2007, Akay and Ipek 2010)

$$R(w) = \frac{1}{n}\sum_{i=1}^{n} \left| y_i - f(x_i) \right|_{\varepsilon} + C\|w\|^2 \tag{1}$$

With ε-insensitive model

$$\left| y_i - f(x_i) \right|_{\varepsilon} = \begin{cases} 0 & if \left| f(x_i) - y_i \right| \le \varepsilon \\ \left| f(x_i) - y_i \right| - \varepsilon & else \end{cases} \tag{2}$$

Moreover, by introducing the nonnegative slack variables $\{\xi_i\}_{i=1}^{n}$ and $\{\xi_i^*\}_{i=1}^{n}$, subjecting to the constraints

$$\begin{cases} y_i - < w, \phi(x_i) > - b \le \varepsilon + \xi_i \\ < w, \phi(x_i) > + b - y_i \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0, i = 1, 2 \ldots N \end{cases} \tag{3}$$

The optimization problem can be formulated in the primal space with the following equation

$$\frac{1}{2}\|w\|^2 + C\frac{1}{n}\sum_{i=1}^{n}(\xi_i + \xi_i^*) \tag{4}$$

Where $\|\cdot\|$ denotes the Euclidean norm, ε is the maximal value of tolerable error, C is a generalized constant that represents a trade-off between the model complexity and the tolerance to the error larger than ε.

Maximizing the following optimum problem

$$-\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}(a_i - a_i^*)(a_j - a_j^*) < \phi(x_i), \phi(x_j) > -\varepsilon\sum_{i=1}^{N}(a_i + a_i^*) + \sum_{i=1}^{N} y_i(a_i - a_i^*) \tag{5}$$

Subjecting to the constraints

$$\begin{cases} \sum_{i=1}^{N}(a_i - a_i^*) = 0 \\ a_i, a_i^* \in [0, C] \end{cases} \tag{6}$$

The model parameter vector w can be obtained

$$w = \sum_{i=1}^{n}(a_i - a_i^*)\phi(x_i) \tag{7}$$

If a function satisfies Mercer's condition, it can be used as kernel function , and the kernel function equals the inner product of two vectors x_i and $x_j$in the feature space $\phi(x_i)$ and $\phi(x_j)$, that is $K(x_i, x_j) = < \phi(x_i), \phi(x_j) >$ (Vapnik 1999).

For the support vectors, the model becomes

$$f(x_i) = \sum_{j=1(j\in SV)}^{N_{SV}}(a_i - a_i^*)K(x_i, x_j) + b \tag{8}$$

Where N_{SV} denotes the number of support vectors in the model.

There exist several choices of kernel function K like that linear, polynomial and Gaussian radial basis function. Generally, Gaussian kernel function can obtain better prediction performance. Therefore, the Gaussian kernel function is used as the SVR model kernel function in this study and it is defined below

$$K(x_i, x_j) = \exp\{-\left|x_i - x_j\right|^2 / \sigma^2\} \tag{9}$$

Where σ is the bandwidth of the kernel function.

For constructing a more reliable SVR model, the regressive parameters must be set carefully; inappropriate parameters in SVR may produce a worse performance SVR model and over-fitting or under-fitting problem. For the SVR model based on Gaussian kernel, the parameters C, σ and ε are required to be selected carefully. Hereby, grid search is used to optimize above proposed parameters, and improve the reliability of the SHM system (Zhang *et al.* 2006).

3. Experimental investigation

3.1 Impact experimental setup

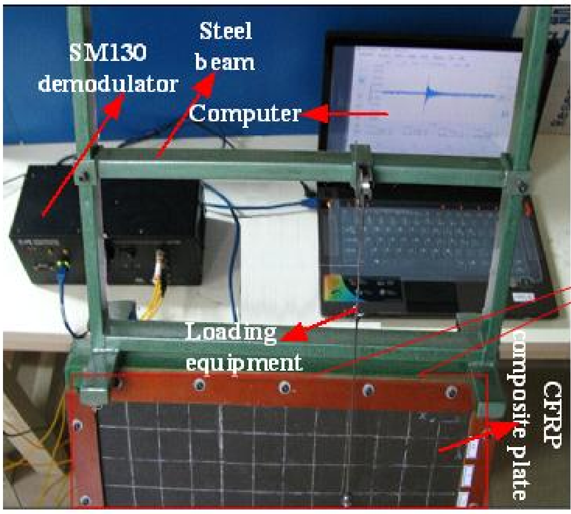
The periodic structure of the fiber Bragg grating is formed by photo induced periodic refractive index modulation within the fiber core, which results in a series of grating planes formed along the fiber axis. If the Bragg condition is met, the reflectivity of the grating planes for the incident light will form a back reflected signal with a central wavelength that is known as Bragg central wavelength (λ_B) (Yeo *et al.* 2005). With this, λ_B can be expressed as $\lambda_B = 2n_{eff}\Lambda$, Where Λ is the period of the grating plane, n_{eff} is the effective refractive index of the fiber core (Kerrouche *et al.* 2009). The period change of the grating plane is sensitive to a number of physical parameters such as strain, temperature, pressure, ultrasound, high magnetic field, force and vibration. Thereby, by virtue of monitoring the resultant change in reflected wavelength, FBG sensor can be used in various sensing applications to measure physical parameters. If temperature change is negligible, then the shift of the central wave length spectrum basically reflects the change in the stress and strain status on the FBG. So the FBG sensor network can measure not only a low-frequency signal with large magnitude such as strain but also a high-frequency signal with small amplitude such as damage or impact signal which will be required for the structural health monitoring (Herszberg *et al.* 2005).

A SHM system for monitoring the foreign-object low velocity impact of a CFRP composite plate with a FBG sensor network is experimented. The CFRP composite plate length of 600 mm, width of 600 mm and thickness of 2.16 mm, it is manufactured withT300/QY8911, four sides of the plate is fixed by the screw and frame with width of 30 mm, so the effective area of inflicting impacting loads is 540 mm×540 mm. The experimental setup is presented in Fig. 1. The impacting pendulum is fixed on the steel beam, and it can move along the beam freely, simultaneously, the steel beam can move up-down freely. In this way, any position of the CFRP composite plate can be inflicted impacting loads. For obtaining the training samples and testing samples that the SVR model needed, the composite plate is divided into 11 rows and 11 columns altogether 121 cells which length and width are both 45 mm, and the impacting loads are inflicted on the row-column intersections. The different position of the CFRP plate is subjected to artificial impact generated by dropping a small ball which diameter is 20 mm and quality is 5.03 g, the pendulum length and angle of the impact load are 900 mm, 52° and 60° separately which are applied to the intersectional position of the composite plate. After that, FBG sensors (Fig. 2) that are mounted on the CFRP composite plate receive the impacting wave when the strain change depending on time, the center wavelength of the reflected light from the FBG will change. And the impacting signals from multiple FBG sensors are sampled and the Bragg central wavelength shifts are viewed by the high-speed optical wavelength interrogation system SM130, a computer with data acquisition software (Lab View) for flexibility in data will display, process, and storage all of information observed.

3.2 Impacting signal feature extraction

If the impacting load inflicts on the central of the CFRP composite plate, Fig. 3 shows the waveform obtained by the FBG1.

It is difficult to directly predict the impacting position from the measured waveforms. Hence, Fourier transform is applied to the waveforms for frequency analysis, and the transforming results of every FBG sensor for the inflicting impact on the central position of the plate depending on amplitude and frequency are displayed in Fig. 4. These results show that the values of amplitude decrease with the frequency increasing, and the larger amplitude mainly centralize between 0 Hz and 200 Hz. Therefore, the band energies of the waveforms are calculated depending on the amplitude of 0-200 Hz frequency, and the band energy is calculated as: $E(i) = \frac{1}{N}\sum_{n=0}^{N-1}\left|x_i(n)\right|^2$, where N is the sum of total number of sampling points, $x_i(n)$ is the i th sampling point value, the calculating results are shown in Fig. 5.



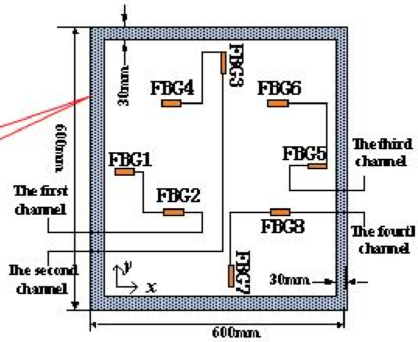


Fig. 1 Impact experimental setup based on FBG sensor network and Fig.2 Arrangement of sensors in the plate

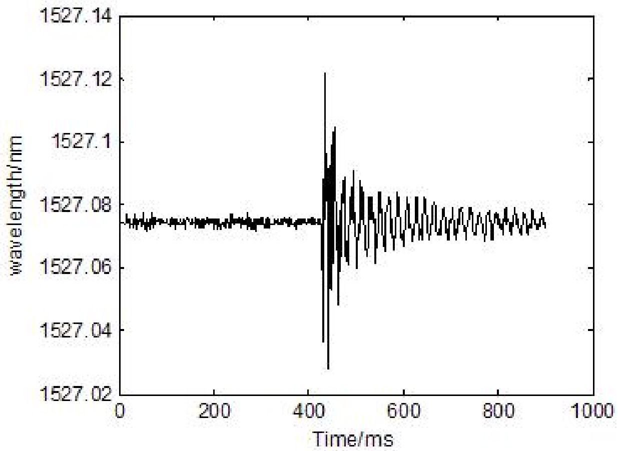


Fig. 3 Response of FBG1to an impact observed at the central of the plate

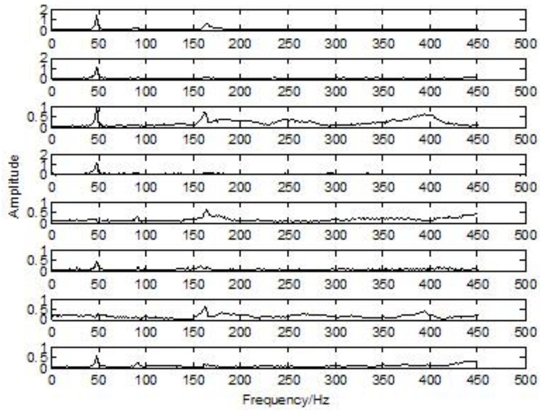


Fig. 4 Fourier transforms of FBG1 to FBG8impactsignals for the central position

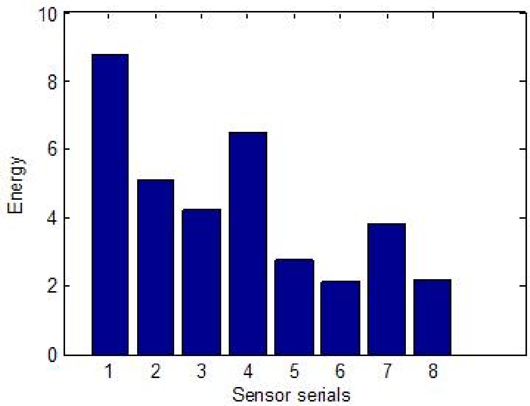


Fig. 5 Band energies of FBG1 to FBG8impacingt signals (0-200 Hz)for the central position

In this way, the band energies for every FBG sensor on any inflicting impacting positions are calculated, the calculated results indicate that the value of the band energies for every FBG sensor in different impacting positions are different, so the band energy can be used for the feature of the impacting signals to train the SVR model and to predict any impacting load positions on the CFRP plate.

3.3 SVR model reconstruction scheme for SHM

For SHM system, many FBG sensors can be incorporated within a single fiber, and measurement makes from either end of the optical fiber, this type of single-ended topology has been discussed and demonstrated by a lot of investigators (Moyo *et al.* 2005, Chan *et al.* 2006). However, this topology is not designed for the network reliability and survivability that require the network working as normal if fibers, nodes, or sensors link fail, this becomes especially worrisome when they are arranged to monitor the hostile environments such as dams or submarines. Recently, how to build a high reliability FBG sensor network becomes an important issue for the SHM system.

So as to improve the reliability of the SHM system, a model reconstruction recognition algorithm based on SVR is proposed in this study. In the SHM system, FBG sensors are arranged with redundant. For one thing, the redundancy can improve the predicting accuracy of the monitoring system, for the other thing, it can compensate for the sensor data if partial sensors are invalid in the sensor network. The model reconstruction scheme is shown in Fig. 6. It works like this: Firstly, if each sensor in the SHM system is valid and their signals can be demodulated correctly, SVR model can be trained by the impacting signal feature values of the central wavelength change acquired by the demodulator, and the SVR model A is obtained. Here if an impacting load inflicts on the CFRP composite plate, model A is used for predicting the impacting load position. Secondly, if an FBG sensor is invalid in the monitoring system (neglecting certain FBG sensor data to simulate the failure mode), the SVR model is retrained by virtue of the sensor data that can be demodulated by the FBG demodulator, and the SVR model is called model B. Simultaneously, model B is treated as model A to predict the future impacting load position. For the rest failure mode such as sensor n^{th},$(n\text{-}1)^{th}$, $(n\text{-}2)^{th}$…, which can be done in the same way.

3.4 Experimental results and discussions

In the experimental area, 121 positions are chosen to inflict impacting load which energies are 22.182 mJ and 27.314 mJ separately, thus 121 samples are obtained for each energy level. In this study, the 121 samples of 22.182mJ level are chosen as the training samples, the others are chosen as the testing samples.

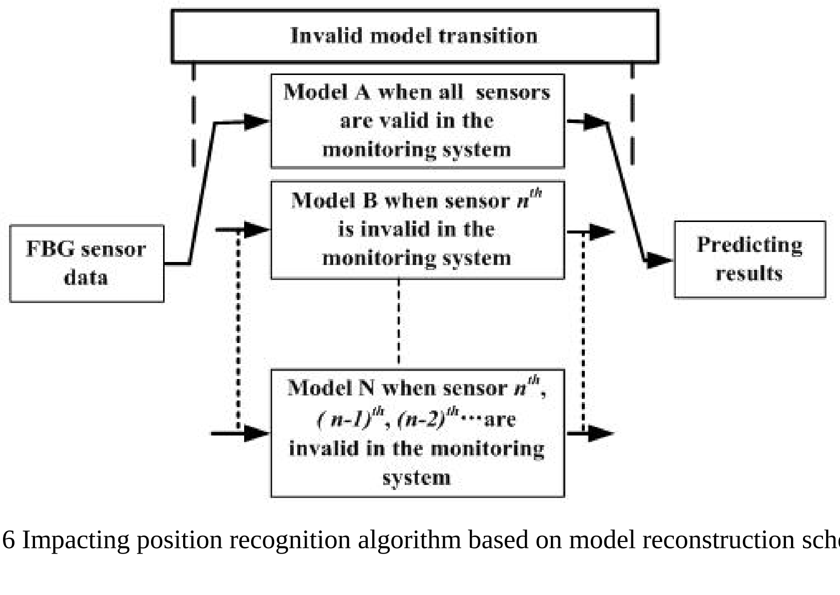


Fig. 6 Impacting position recognition algorithm based on model reconstruction scheme

For improving the generalization capability of SVR model, the FBG sensor feature values of the impacting signal in different position of the plate are normalized to [0, 1], and the training samples and testing samples are normalized separately. The predicting step is as follow: (1) the SVR model's free parameters of x-coordinate and y-coordinate are optimized by the training samples; (2) the x-coordinate training samples and y-coordinate training samples are trained by the obtained optimal parameters separately, meanwhile, their corresponding SVR models are obtainde; (3) the x-coordinate and y-coordinate testing samples are predicted separately, the distance error between actual value and predicting value (DEBAP) is used to evaluate the predicting accuracy and determine the effectiveness of the established SVR model. Here, the DEBAP is described as: $DEBAP = \sqrt{(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2}$. Where x_i and $\hat{x}_i$ represent the *i*th x-coordinate actual and predicting value respectively, y_i and $\hat{y}_i$ represent the *i*th y-coordinate actual and predicting value respectively. For the impacting position monitoring, the permissible predicting distance error (DEBAP) requires less than 45 mm. If one sensor or two sensors are invalid in the FBG sensor network, sensor *6th*, sensor *7th,* sensor *1st*, *4th* and sensor *6th*, *7th* are neglected separately to simulate these two kinds of failure modes, the model reconstruction scheme which is proposed in Fig. 6 is used to retrain the SVR model by the corresponding valid FBG sensor data. Then the impacting load position of the testing sample is predicted with the obtained SVR model, moreover, the result is compared with non-reconstruction respectively. The DEBAP of predicting samples from 12*th* to 41*st* are graphically demonstrated in Figs. 9 -11. As a result, In spite of which one or two sensors is invalid in the FBG sensor network, the performance of the SVR model reconstruction has more excellent than that of non-reconstruction. Here, Non reconstruction denotes whether there are some sensors invalid in the FBG sensor network or not, only model A is used to predict the future unknown external loading damage position, and the DEBAP values are calculated by model A. Reconstruction works like above Fig. 6, correspondingly, the DEBAP values are calculate by model *B……N.*

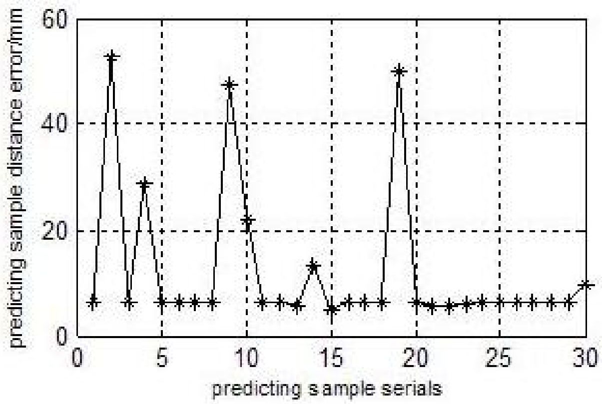


Fig. 7 Distance error for no sensor is invalid

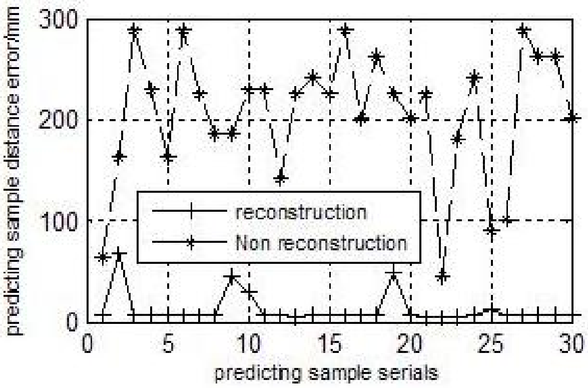


Fig. 8 Distance error for sensor 6^{th} is invalid

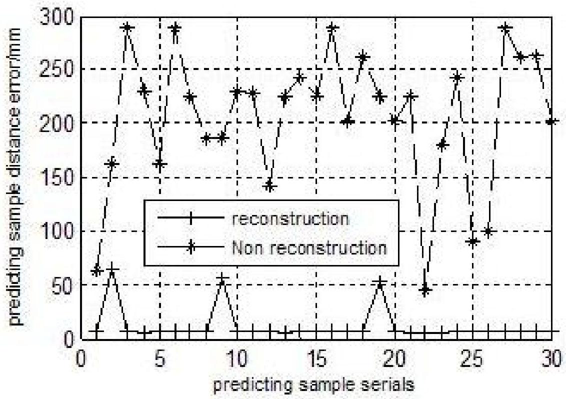


Fig. 9 Distance error for sensor 7^{th} is invalid

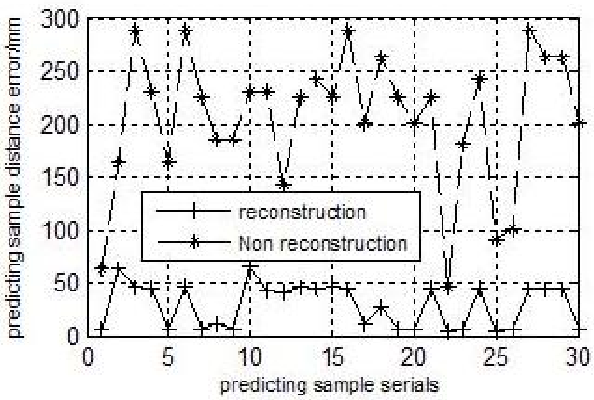


Fig. 10 Distance error for sensor 1^{st}, 4^{th} are invalid

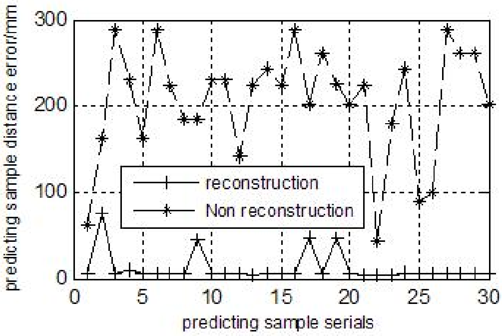


Fig. 11 Distance error for sensor 6^{th}, 7^{th} are invalid

For demonstrating the number of FBG sensors needed least when the SHM system can work as normal, one, two, three or four sensors are neglected to simulate different FBG sensor network failure modes. For each failure mode, three or four kinds of patterns are randomly selected to investigate the predicting accuracy of the SHM system, and the results are compared with non-reconstruction respectively. The comparative results are given in Table 1.

Table 1 the comparison of the predicting results by reconstruction and non-reconstruction

Monitoring system condition	Sample counts ratio Reconstruction	Sample counts ratio Non-reconstruction	Monitoring system condition	Sample counts ratio Recon struction	Sample counts ratio Non-recon struction
No sensor is invalid	89.3%	89.3%	Sensor $6^{th}$is invalid	88.4%	13.2%
Sensor $7^{th}$is invalid	88.4%	8.3%	Sensor $4^{th}$is invalid	86.8%	9.1%
Sensor $1^{st}$is invalid	86.8%	5.8%	Sensor 3^{rd}, $4^{th}$are invalid	86.8%	4.13%
Sensor 1^{st},$4^{th}$are invalid	85.1%	4.13%	Sensor 6^{th}, 7^{th} are invalid	84.3%	4.13%
Sensor 1^{st}, $7^{th}$are invalid	84.3%	4.13%	Sensor 1^{st}, 7^{th}, $8^{th}$are invalid	80.2%	4.13%
Sensor 1^{st}, 6^{th}, 7th are invalid	75.2%	4.13%	Sensor 1^{st}, 2^{nd}, $6^{th}$are invalid	69.4%	4.13%
Sensor 1^{st}, 2nd, 7th are invalid	69.4%	4.13%	Sensor 1^{st}, 4^{th}, 6^{th}, $7^{th}$are invalid	67.8%	4.13%
Sensor 1^{st}, 2^{nd}, 7^{th}, $8^{th}$are invalid	54.5%	4.13%	Sensor 3^{rd}, 4^{th}, 5^{th}, $6^{th}$are invalid	5.8%	4.13%

(Note: Sample counts ratiodenotes the samples that less than or equal to 45mmcounts /total sample counts (121))

For the reconstruction, when one and two sensors are invalid in the FBG sensor network, the ratio that less than or equal to 45 millimeter counts account for the total sample counts only decrease 2.5% and 5% to the full extent separately comparing with that no sensor is invalid in the FBG sensor network. When three and four FBG sensors are invalid in the FBG sensor network, the ratio decrease obviously comparing with that no sensor is invalid in the FBG sensor network, at the same time, the largest declining are 19.9% and 83.5% separately. However, for the non-reconstruction, one sensor is invalid in the network will make the predicting distance error (DEBAP) too big and the SHM system can't work as normal. For the same numbers and different invalid FBG sensors assembly in the network, the predicting accuracy is different. For example, the predicting accuracy of assembly sensor 1^{st}, 4^{th}, 6^{th}, 7^{th} is more than 62 percentages above sensor 3^{rd}, 4^{th}, 5^{th}, 6^{th}. The results indicate that the placement of the sensor arrangement plays an important part role in the SHM system. Therefore, it is vital to optimize the sensor placement before mount on or embedded the monitoring structure.

4. Conclusions

For the structural health monitoring, FBG sensor network is mounted on or embedded in the structure with series or parallel. If fiber node is invalid, the FBG sensor can't be demodulated behind the invalid point. With the wide application of FBG sensor network in the SHM system, it is necessary to improve the survivability and reliability of the FBG sensor network. In this study, a model reconstruction recognition algorithm based on SVR is proposed to achieve the high reliable FBG sensor network. Meanwhile, a SHM system for monitoring the foreign-object low velocity impacting position of a CFRP composite plate is designed to verify the reliability of the FBG sensor network. For the permissible predicting distance error (no more than 45 millimeter), when one and two sensors are invalid in the FBG sensor network, the sample counts ratios only decrease 2.5% and 5% to the full extent comparing with that no sensor is invalid in the system, but for the non-reconstruction, the least declining ratios are 76.1% and 85.17%.These studies successfully demonstrate that the proposed model reconstruction algorithm based on SVR almost keep the consistent predicting accuracy when no, one and two sensors are invalid in the FBG sensor network, and the survivability and reliability of the SHM system are improved. For the different invalid FBG sensor position, this study also find that the predicting accuracy is different for the same numbers invalid FBG sensors. So it is necessary to consider the sensor arrangement position in the monitored structure in future.

Acknowledgements

The research described in this paper was financially supported by National Natural Science Foundation of China (Grant Nos. 51275239 and 61201109), National Natural Science Fund of International Communication (51161120326), Science and Technology Support Project of Jiangsu Province (Grant No. BE2011181), Fund of Aeronautics Science (Grant No.20125652055 and 2011ZA52013), Higher School Specialized Research Fund for the Doctoral Program (Grant No.20123218110003), A Project Funded by the Priority Academic Program Development of Jiangsu Higher Education Institutions, Science and Technology Planning Project of Henan Province (Grant No. 142102210482), Science and Technology Research Key Project of Education

Department of Henan Province (Grant No. 13A510770), Project supported by the Young Core Instructor from Xinyang Normal University. The State Key Laboratory of Mechanics and Control of Mechanical Structures are acknowledged for providing optical fiber sensors and relative devices.

References

Akay, M.F. and Ipek, A. (2010), "Predicting the performance measures of an optical distributed shared memory multiprocessor by using support vector regression", *Expert Syst. Appl.*, **37**(9), 6293-6301.

Andres, A.T., Alberto, A.S. and Sen, R.J. (1998), "Galvanic interaction between carbon fiber reinforced plastic (CFRP) composites and steel in chloride contaminated concrete", *Proceedings of the 1998 NACE International Conference*, Houston, Aug.

Ankit, B.G., JoshiJ, B., Valadi, K.J. and Bhaskar, D.K. (2007), "Development of support vector regression (SVR)-based correlation for prediction of overall gas hold-up in bubble column reactors for various gas–liquid systems", *Chem. Eng. Sci.*, **62**(7), 7078-7089.

Chan, T.H.T., Yu, L., Tam, H.Y., Ni, Y.Q., Liu, S.Y., Chung, W.H. and Cheng, L.K. (2006), "Fiber Bragg grating sensors for structural health monitoring of Tsing Ma bridge: Background and experimental observation", *Eng. Struct.*, **28**(5), 648-659.

Dai, Y.B., Liu, Y.J., Leng, J.S., Deng, G., and Asundi, A. (2009), "A novel time-division multiplexing fiber Bragg grating sensor interrogator for structural health monitoring", *Opt. Laser. Eng.*, **47**(10), 1028-1033.

Guo, Z.W. and Bai G.C. (2009), "Application of least squares support vector machine for regression to reliability analysis", *Chinese J. Aeronautics*, **22**(2), 160-166.

Hoschke, N., Lewis, C.J., Price, D.C., Scott, D.A., Gerasimov, V. and Wang, P. (2008), *A self-organizing sensing system for structural health monitoring of aerospace vehicles*, Advanced Information and Knowledge Processing, Part II: 51-76.

Herszberg, I., Li, H.C.H., Dharmawan, F., Mouritz, A.P., Nguyen, M. and Bayandor, J. (2005), "Damage assessment and monitoring of composite ship joints", *Compos. Struct.*, **67**(2), 205-216.

Hu, X.L., Liang, D.K., Zeng, J. and Lu, G. (2010), "A long period grating for simultaneous measurement of temperature and strain based on support vector regression", *J. Intel. Mat. Syst. Str.*, **21**(10), 955-959.

KapilS, B. (2010), "On Lagrangian support vector regression", *Expert Syst. Appl.*, **37**(12), 8784-8792.

Kerrouche, A., Boyle, W.J.O., Sun, T. and Grattan, K.T.V. (2009), "Design and in-the-field performance evaluation of compact FBG sensor system for structural health monitoring applications", *Sensor. Actuat. A - Phys.*, **151**(2), 107-112.

Maaskant, R., Alavie, T., Measures, R.M., Tadros, G., Rizkalla, S.H. and Guha-Thakurta, A. (1997), "Fiber-optic Bragg grating sensors for bridge monitoring", *Cement Concrete Comp.*, **19**(1), 21-33.

Mieloszyk, M., Krawczuk, M., Zak, A. and Ostachowicz, W. (2010), "An adaptive wing for a small-aircraft application with a configuration of fiber Bragg grating sensors", *Smart Mater. Struct.*, **19**(8), 085009(12pp).

Moyo, P., Brownjohn, J.M.W., Suresh, R. and Tjin, S.C. (2005), "Development of fiber Bragg grating sensors for monitoring civil infrastructure", *Eng. Struct.*, **27**(7), 1828-1834.

Peng, C.P., Wang, J.B. and Huang, K.Y. (2010), "Reliable fiber sensor system with star-ring-bus architecture", *Sensor*s, **10**(8), 4194-4205.

Prokopenko, M., Wang, P., Foreman, M., Valencia, P., Price, D. and Poulton, G. (2005), "On connectivity of reconfigurable impact networks in ageless aerospace vehicles", *Robot. Auton. Syst.*, **53**(1), 36-58.

Scott, D.A., Price, D.C., Hoschke, N. and Richards, W.L. (2009), "Structural health monitoring of thermal protection systems", *Mater. Forum*., **33**, 457-464.

Vapnik, V.(1999), *The nature of statistical learning theory*, Springer, USA.

Yang, Z., Gu, X.S., Liang, X.Y. and Ling, L.C. (2010), "Genetic algorithm-least squares support vector regression based predicting and optimizing model on carbon fiber composite integrated conductivity",

Mater. Design, **31**(3), 1042-1049.
Yeh, C.H., Chow, C.W., Wang, C.H., Shih, F.Y., Wu, Y.F. and Chi, S. (2009), "A simple self-restored fiber Bragg grating (FBG)-based passive sensing ring network", *Meas. Sci. Technol*., **20**(4), 043001 (5pp).
Yeo, T.L., Sun, T., Grattan, K.T.V., Parry, D., Lade, R. and Powell, B.D. (2005), "Characterization of polymer-coated fiber Bragg grating sensor for relative humidity sensing", *Sensor. Actuat. B - Chem*., **110**(1), 148-155.
Zhang, J., Sato, T. and Susumu, I. (2006), "Support vector regression for on-line health monitoring of large-scale structures", *Struct. Saf.*, **28**(4), 392-406.

CC