Smart Structures and Systems, *Vol. 14, No. 2 (2014) 129-144*
DOI: http://dx.doi.org/10.12989/sss.2014.14.2.129

The application of a fuzzy inference system and analytical hierarchy process based online evaluation framework to the Donghai Bridge Health Monitoring System

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(Received June 10, 2012, Revised March 25, 2013, Accepted July 29, 2013)

Abstract. In this paper, a fuzzy inference system and an analytical hierarchy process-based online evaluation technique is developed to monitor the condition of the 32-km Donghai Bridge in Shanghai. The system has 478 sensors distributed along eight segments selected from the whole bridge. An online evaluation subsystem is realized, which uses raw data and extracted features or indices to give a set of hierarchically organized condition evaluations. The thresholds of each index were set to an initial value obtained from a structure damage and performance evolution analysis of the bridge. After one year of baseline monitoring, the initial threshold system was updated from the collected data. The results show that the techniques described are valid and reliable. The online method fulfills long-term infrastructure health monitoring requirements for the Donghai Bridge.

Keywords: health monitoring; Donghai Bridge; online evaluation; analytical hierarchy process; fuzzy inference system

1. Introduction

In the last two decades many integrated bridge health monitoring systems have been implemented. Multiple mechanical and physical measurements are continuously made in real-time by a variety of remote sensing techniques. Many integrated infrastructure health monitoring systems are well designed and implemented. As the extent of integration increases, more functions are added into the system, more functionality is specified by system designers and researchers, and the definitions of structure health monitoring systems are continuously improved (Los Alamos National Laboratory report 2003, Hsieh *et al.* 2006). Three generations of the structural health monitoring system (SHMS) are recognized. In the first generation, measurement is discontinuous and only a few kinds of sensing apparatus are installed. The second generation, the so-called integrated health monitoring system, uses multiple-sensor subsystems, data acquisition, communication and software control systems to run the functions of data storage and management,

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

and simple data processing and display. Unfortunately, the utilization of this painstakingly gathered and expensive data is still low or nil, with most research being done on the data offline and after a long time lag. Third generation SHMS are expected to have a capacity for using the data for multiple purposes in real time, allowing online infrastructure health status evaluation.

Although these three generations of structural health monitoring systems for bridges (hereinafter referred to as BHMS) are expected to meet original motivations such as validation of design, ensuring the security and normal operation of the structures, and finding new knowledge about the performance of the structures, these targets are not yet routinely achieved. There is still much work to be done to take raw monitoring data and process it to achieve aims such as local damage identification, and assessment of structural conditions. From the viewpoint of bridge owners and designers, optimized bridge maintenance and management is a high priority aim for a BHMS. Objective judgments of bridge health and safety status aided by BHMS are urgently required (Ou *et al*. 2006).

Early bridge management systems used evaluation technologies. By using inspection information and Non Destructive Testing (NDT) results, rating techniques were introduced to give reasonable and systemic judgments concerning the safety, serviceability and durability of the bridge, allowing objective and optimized decisions on bridge maintenance and management. To give a reasonable evaluation, an analytical hierarchy process is used to assess numerous items of data, and computing techniques such as fuzzy evaluation technologies, neural net computing and Bayesian probabilistic approaches are used to improve rationality and veracity (Liang *et al.* 2001, Ratay and Wiley 2005).

To incorporate present structural condition assessment techniques into a bridge health monitoring system with a real-time online evaluation mechanism is an urgent requirement. In this paper, a fuzzy inference system (FIS) using an analytical hierarchy process (AHP) is used to create an online bridge evaluation system. Information from the real-time monitoring system and more subjective information from inspection routines are organized in a hierarchical architecture and data fusion between the two sorts of information and reasoning processes are realized in a fuzzy interference system. The technologies presented here are installed as an online evaluation subsystem of the Donghai Bridge Health Monitoring System (DHBHMS).

2. The Donghai Bridge Health Monitoring System

Donghai Bridge (Fig. 1) links Luchao Port in Shanghai and the Yangshan Island Deep Water Port in Zhejiang Province. The bridge is about 32 km long and consists of 2 cable-stayed bridges and a large number of continuous and simply supported bridge spans. Donghai Bridge is the first large scale bridge across a stretch of sea in China (Huang 2004).

The goals of the Donghai Bridge Heath Monitoring System (DHBHMS) are as follows:

1) To monitor the performance and the operating condition of the bridge, both in real-time monitoring and by periodical inspection.

2) To ensure the safety and normal service conditions of the structure.

3) To supply objective scientific data and decision support for bridge maintenance and management.

Fig. 1 Donghai Bridge, Shanghai, China

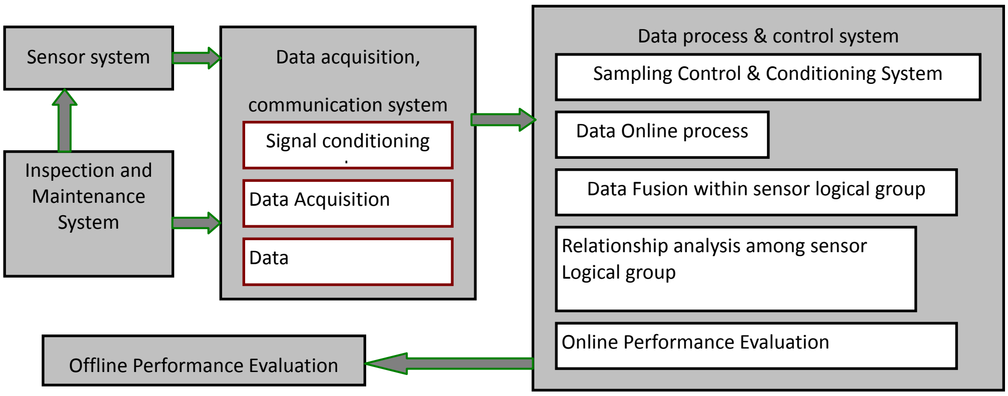


Fig. 2 The modular structure of the DHBHMS

The underlying principle of the design of the DHBHMS is performance monitoring. The layout of the sensors and the selection of the items to be monitored are related to the needs of bridge performance monitoring. Similarly, the data process and online evaluation subsystems are designed to meet the needs of judging safety and the normal service conditions of the structure during operation. Precautionary data analysis and an offline evaluation scheme are required to meet the needs of bridge maintenance and management as well as the requirements of scientific research.

Based on these general considerations, the DHBHMS (Danhui and Sun 2004) was designed and installed in April, 2006. The 478 sensors are distributed along eight segments selected from the whole bridge structure. Browser/Server based software is realized to measure the target quantities, monitor selected features extracted from the raw data in real-time, and to store and manage the data. Critically, an online evaluation subsystem is realized, which uses the raw data and the features (modal parameters or other indices) extracted from the data to give a set of condition evaluations organized in a hierarchical structure. The modular structure of the DHBHMS is illustrated in Fig. 2.

This paper describes the first attempt in China to use monitoring and inspection data to support safety judgments and structural health status assessment by means of automatic online bridge health evaluation. The AHP (analytical hierarchy process) was used to organize the evaluation hierarchy tree structure, and an autonomous network-based Fuzzy Inference System (ANFIS) technique is used to perform inference in each knot (marking the end of one region of data and the beginning of another) of the tree. Scores at each knot are transferred to the level above in the tree. Finally, an ultimate score can be calculated and a report can be generated to support human decision-making.

3. An AHP and FIS based online evaluation framework

As previously mentioned, the DHBHMS covers the whole 32 km of the bridge including continuous beam spans and two cable-stayed bridges. The captured data are vast and complex, and so must be organized into a suitable architecture for interpretation.

First the sensors installed on the bridge are organized into logical groups. For example, Global Positioning System (GPS) sensors, displacement sensors for extension gaps, connected pipe sensors detecting uneven settlement and deflections in mid span, can be grouped to monitor the whole geometric shape of the bridge, and also can be composed into a global geometric configuration logical group. Similarly, the vertical direction acceleration sensors on the beams can be composed into a vertical mode monitoring group. The inspection information is also organized into logical groups according to physical function. Fig. 4 gives the layout of the sensors on the main navigation channel cable stayed bridge. Table 1 gives detail of some of the logical groups of the main navigation channel cable-stayed bridge.

Table 1 Some sensor logical groups in the main navigation channel cable-stayed bridge

Logical groups	Location	Sensors	Target quantities in the group
Wind field monitoring group	Top tower, middle of mid span	Ane	Mean wind speed, wind pressure, gust wind speed. The spectral features of different directions
System temperature of the beam	All the temperature sensors	St	To estimate the temperature distribution alone the whole bridge
Temperature grads monitoring group	Section 7 at beam Section 2 at tower	St, At	To estimate the temperature distribution inner same sections
Local deformation monitoring group	Section 7 at beam End sections at beam	GPS Fi	Get the deflection of the beam and other indirect quantities
Global deformation monitoring group	The whole bridge	GPS Fi	To estimate the global deformation of the bridge
Strain monitoring group	The strain installed in same sections	Str	Estimate the inner force under live load, vildate the hypotheses of even section, and the statistical feature of them.
Vertical mode monitoring group	Vertical acceleration in beam	Acc	To monitor the magnitudes level of the bridge, and the vertical modal parameters.
Cable force monitoring group	Selected cables	Cf	To monitor able force and estimate the redistribution among the cables, towers, and beam.
Weather monitoring group	Near the bridge	Aws	To estimate the rust situation of the steel components.

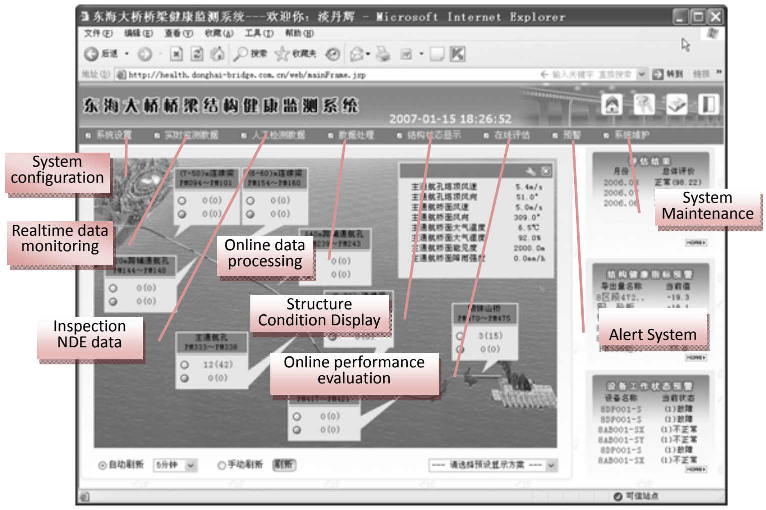


Fig. 3 The DHBHMS client interface (viewed with Microsoft Internet Explorer)

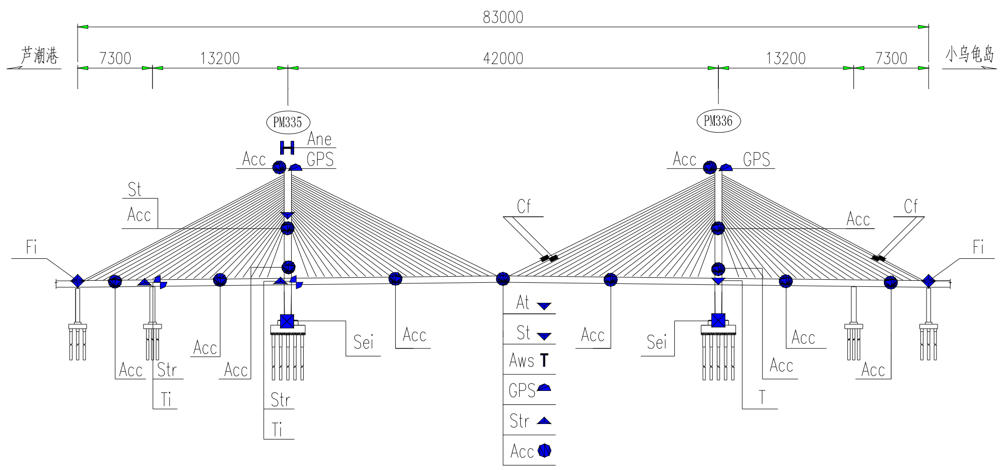


Fig. 4 The layout of the sensors on main navigation channel cable-stayed bridge At—atmosphere temperature sensor (1); St—structural temperature sensors (46)； Ane—Anemometer (1); Aws-weather station (1); GPS—GPS (3)； Str—FBG strain gauges (48)； Acc—acceleration meter (27); Sei-strong vibration accelerometer; (2); Ti—fatigue meters (24); Fi—extension gauges (4); Cf—cable force apparatus (8)

The whole online evaluation is designed as a hierarchical tree structure. The lowest layer has the sensors and inspection items; each knot in this layer represents a channel in the real-time monitoring system or a virtual channel from the secondary quantities processed from actual channel data, or from inspection. In the first layer, the raw data act as representation patterns, the feature selection and extraction operations are conducted to reduce the data dimensions and data compression. In doing this, the original data from each logical group are processed, with the aim to obtain several meaningful indices. Both the number and the length of the indices are smaller than the original data, but the useful information are more condensed. For example, in vertical mode monitoring group, 14 channels acceleration records are processed into modal flexibility matrix by means of modal parameter identification process, and the elements which contains the most information of dynamic features are selected. Both the length and dimensions of the extracted indices is far smaller than original acceleration record.

The second layer is the logical group layer, and the fuzzy inference system (FIS) is used to realize inference from the feature patterns to form the ratings or scores of the logical group. FIS have a capacity to integrate different types of quantities into one set of linguistic quantities, the inputs are objective numerical data measured from sensors and the other inputs are subjectively determined by the inspectors' experience and intuition (Danhui 2004, 2006). This is therefore a highly suitable case for conducting data fusion between monitoring and inspection information. The third layer is the reliability evaluation layer where safety, durability and serviceability are evaluated simply by a set of systematic rating scores. The fourth layer is the segment evaluation layer with inputs composed of three overall scores for safety, durability and serviceability. The final layer describes the whole bridge. This global score for the whole bridge supports human decision-making, and is based on the inference engines of the underlying layers in weighted accumulation of input.

By means of feature S&E (selection and extraction), FIS, and weighted accumulations, the information flows from the lowest layer to highest layer, and the raw data are processed, extracted, and condensed as final scores, which help to give the whole bridge an general description and judgment.

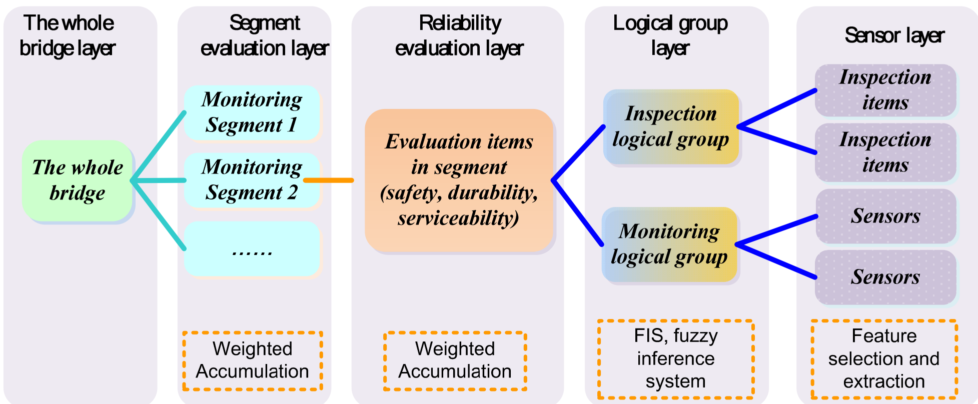


Fig. 5 The AHP based online evaluation tree of DHBHMS

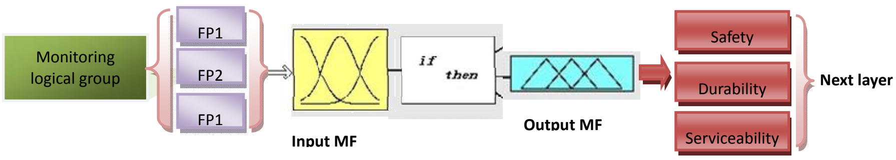


Fig. 6 The architecture of the FIS engine (Feature Pattern, abbr. FP)

The architecture of the FIS engines is illustrated in Fig. 6. For the convenience of programming, the initial antecedent membership function (MF) is selected as follows

$$\mu_{\text{small}}(x)=\begin{cases}1 & x\le a\\ \dfrac{b-x}{b-a} & a\le x\le b\\ 0 & b\le x\end{cases} \tag{1a}$$

$$\mu_{\text{modest}}(x)=\begin{cases}0 & x\le \dfrac{a+b}{2}\\ \dfrac{x-0.5(a+b)}{0.5(c-a)} & \dfrac{a+b}{2}\le x\le \dfrac{b+c}{2}\\ \dfrac{0.5(c+d)-x}{0.5(d-b)} & \dfrac{b+c}{2}\le x\le \dfrac{c+d}{2}\\ 0 & \dfrac{c+d}{2}\le x\end{cases} \tag{1b}$$

$$\mu_{\text{large}}(x)=\begin{cases}0 & x\le c\\ \dfrac{x-c}{d-c} & c\le x\le d\\ 1 & d\le x\end{cases} \tag{1c}$$

Where the μ is the membership function and its subscript 'small', 'modest', and 'large' represent the three levels of descriptions for a given antecedent domain 'x'; and parameters 'a', 'b', 'c', and 'd' are key points in antecedent domain 'x', which can be determined according to what the 'x' is.

The consequent MF are selected as follows

$$gaussian\{x;c,\sigma\}=e^{-\frac{1}{2}\left(\frac{x-c}{\sigma}\right)^2} \tag{2}$$

Where the 'x' here represents the consequent domain variables and 'c' and 'σ' is the parameters who described the feature of distribution of 'x', also can be determined and adjusted by experience.

Initial rules for the kernel engine for online evaluation system are as follows,

Table 2 Initial rules for FIS engines

Rules	FP1	FP2	Conclusion
Rule 1	Small	Small	Good
Rule 2	Small	Modest	Good
Rule 3	Small	Large	Ordinary
Rule 4	Modest	Small	Good
Rule 5	Modest	Modest	Ordinary
Rule 6	Modest	Large	Bad
Rule 7	Large	Small	Ordinary
Rule 8	Large	Modest	Bad
Rule 9	Large	Large	Bad

The key to designing a successful evaluation system is to give the index a set of significant and reasonable thresholds, and using these thresholds, the value spaces of the index can be divided into several subspaces, and the evaluation problem itself can be converted to a judgment problem on the value spaces that the index drops into. The initial antecedent MF gives a partition of input space tensioned by selected feature patterns. The parameters in each antecedent membership functions are determined by the initial threshold of the corresponding feature pattern. In expressing (1a, 1b, and 1c), the parameters a, b, c, and d for each feature pattern are designated in advance as follows:

1)The specifications and criteria regulated by the bridge design code, e.g., the mid-span deflection and the displacement in an extension gap have specified limiting values, which can used as a nominal threshold for the corresponding index.

2)The structural analysis result from the process of structural design, e.g., the cable force upper and lower boundaries can be calculated for different load combinations, particularly in the cases of dead load and extreme situation live load combinations.

3)Generally, thresholds of the most selected feature patterns cannot be designated via 1) and 2). Special structural analyses are needed for structural damage and performance evolution analysis (SD&PEA) and are described by the authors elsewhere; the boundaries of modal frequencies can be computed by SD&PEA by assuming reasonable damage scenarios and forecast performance degradation rules and incorporating these into numerical finite element method (FEM) models of the bridge.

Table 3 gives the partial initial thresholds for the feature patterns listed in Table 1 for segment 5, the main navigation channel cable-stayed bridge. The intervals division and correspondence parameters of their membership function is illustrated in Fig. 7.

Table 3 Partial initial thresholds for the feature patterns

Monitoring logical group	*Section/ location*	*Sensor*	*Feature*	*Good (Healthy)*	*Good (Fine)*	*Ordinary (level one)*	*Bad (level two)*
Local deformation logical group	Extension gap 1	Fi	Longitude displacement	By design document and codes			
	Extension gap 2	Fi	Longitude displacement	By design document and codes			
Global deformation monitoring group	Top platform of PM335	GPS	Longitude displacement	[-110,110]mm	[-223,-110]mm [110,223]mm	[-280,-220]mm [223,280]mm	Others
	Top platform of PM336	GPS	Longitude displacement	[-110,110]mm	[-223,-110]mm [110,223]mm	[-280,-220]mm [223,280]mm	Others
	Mid-span	GPS	Vertical deflection	[0,200]mm	[-52,0]mm [200,476]mm	[-110,-52]mm [476,550]mm	Others
Cable force monitoring group	Cable No.24	Cf	Cable force under dead and live load	[5586,6272]kN	[5103,5586]kN [6272,6932]kN	[4116, 5103]kN [6932,7614]kN	Others
	Cable No. 23	Cf	Cable force under dead and live load	[5566,6076]kN	[5081,5566]kN [6076, 6787]kN	[4116,5081]kN [6787,7448] N	Others
	Cable No. 24*	Cf	the relative cable force	[310,380]kN	[275,310]kN [386,462]kN	[200,275]kN [462,500]kN	Others
	Cable No.24**	Cf	the relative cable force	[64.9,73.4]kN	[62.0,64.9]kN [73.4,79.0]kN	[0,62]kN [79,123]kN	Others
Vertical mode monitoring group ***	Acceleration	Acc	Mode frequency (order 1)	[0.366,0.369]	[0.363,0.366], [0.369,0.372]	[0.355,0.363], [0.372,0.378]	Others
	Acceleration	Acc	Mode frequency (order 2)	[0.506,0.512]	[0.501,0.506], [0.512,0.515]	[0.498,0.501], [0.515,0.519]	Others

*,** Corresponding to the relative cable force in case study in section 5. The former is the initial thresholds and the latter is the evolved thresholds defined by the cumulative distribution function of one year's real data. The relative cable force is defined as the distance of cable force from the designed value under dead load to the value under live load and dead

load.
*** Considering geometric and boundary non-linearity, the dynamic characteristics of the bridge shows little variation even in a no-damage situation, so all the factors affecting the inner force distributions can ultimately affect the dynamic characteristics of the bridge. Temperature fluctuations and uneven settlement of supporting piers are taken into account when calculating the mode frequencies using the FEM model. The results show that the total accumulation of all the effects will not exceed 3% for a given mode frequency. The threshold here is a conservative estimate. The estimate may not agree with the observations from on-site measurements because of relative variations of mode frequency due to temperature, the main reason being that the FEM model itself may require further investigation and refinement.

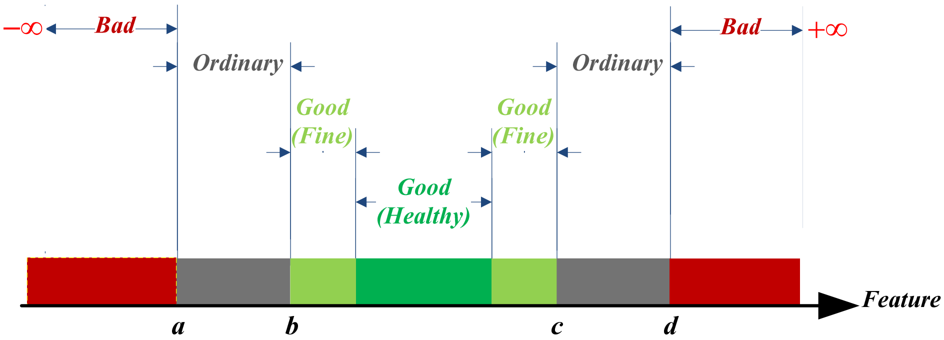


Fig. 7 The intervals division and parameters of membership function

4. Threshold system evolution and updating

The initial threshold system above gives an apriori division of the feature pattern space. The first objective is simply to give a reference to the feature patterns extracted from the raw data. The second is to answer questions from the designer and the bridge operator in the first baseline period of operation, for example, whether or not the bridge is safe, or the design specifications are suitable: these thresholds are conservative estimates.

To give a more precise and reasonable health status evaluation (a division of input feature patterns space), the initial thresholds must be updated and improved based on actual monitored data from the baseline period. In this section, several threshold modifying technologies are discussed. Before updating and evolving the division of pattern space, the feature patterns are re-chosen according actual monitored data. Two methods are used to fulfill these tasks, fuzzy clustering, and statistical pattern recognition. The fuzzy clustering approach is introduced in detail in the following.

As mentioned above, the parameters ‘a’, ‘b’, ‘c’, and ‘d’ in the membership function of the initial input feature patterns a-priori gives its space a meaningful division. If the value space of the input feature pattern has a rich realized samples set, its space can be reduced to a certain extent and the divisions can be made more precise and reasonable. The baseline period is defined as the first year of DHBHMS operation, in which no structural damage occurred.

The space division can be determined by the fuzzy clustering approach, as follows:

- Step I, determining the number of clusters. Here all the realizations of feature patterns come from the baseline period, so it is proposed to be equal to 1.
- Step II, find the central point of each cluster.

- Step III, calculate the difference measure between each single point and cluster central.
- Step IV, divide the feature pattern space according to the distance in step III.

Fuzzy k-mean clustering was described by Dunn in 1974, Chan FTS and Dagdeviren M in 2008, the basic consideration is to allow each sample to have a different membership value to all the clusters. The algorithm of Fuzzy k-mean clustering finds a parameter y_{ij}, (i=1,2,…,n; j=1,2,…,g), which makes

$$J_r = \sum_{i=1}^{n} \sum_{j=1}^{g} y_{ij}^r \left| x_i - m_j \right| \tag{3}$$

under a restriction condition

$$\sum_{j=1}^{g} y_{ij} = 1 \qquad 1 \le i \le n \tag{4}$$

and

$$y_{ij} \ge 0 \qquad i = 1,2,...,n;\ j = 1,2,...,g \tag{5}$$

to obtain a minimum value.

In Eqs. (3)-(5), J_r is the r^{th} value function of fuzzy k-mean clustering; x_i is the i^{th} data sample in vector; y_{ij} is actually the memberships of i^{th} sample (x_i) to j^{th} cluster, r is the weight index to control clustering process. n is number of samples, and g is the total number of clusters. m_j is the central of j^{th} cluster, given by

$$m_j = \frac{\sum_{i=1}^{n} y_{ij}^r x_i}{\sum_{i=1}^{n} y_{ij}^r} \tag{6}$$

There are several measures can be selected as a distance definition. Considering the distance are expected to be measured invariably whatever units the components composed the feature pattern are used, the unit-independent distance measures like Mahalanobis distance should be chosen. Other distance measures like Minkowski or Manhattan are unsuitable here. The definition of the Mahalanobis distance is following

$$d_{ij} = \left(x_i - m_j\right)^T \cdot \Sigma \cdot \left(x_i - m_j\right) \tag{7}$$

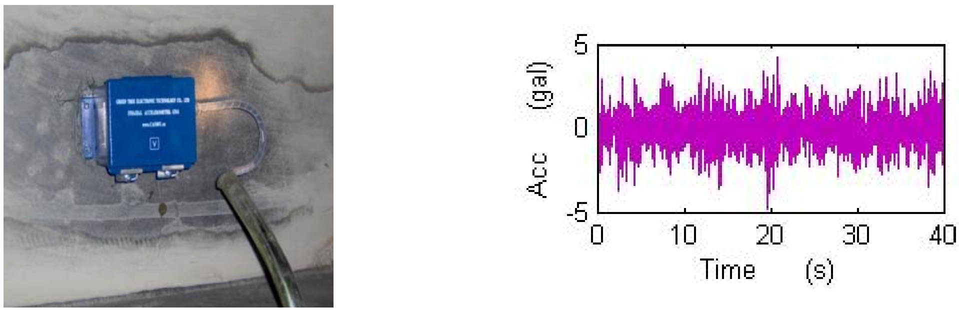
here Σ is covariance matrix of data sample.

The parameters '*a*', '*b*', '*c*', and '*d*' can be easily determined by probabilities in the range [0, $max(d_{ij})$]. Finally, a threshold system can be extracted from the real monitoring data.

To illustrate the above clustering algorithm, the vertical mode monitoring group of segment 5 in the DHBHMS is chosen. Figure 8 gives one of sensors picture and a segmental acceleration records in this group, which located is on the top panel of the girder in middle section. Two days of acceleration recording from this group is used to perform continuous (online) modal parameter identification [20, 21], and the modal flexibility matrix can be calculated by the modal frequency and mode shape. The modal flexibility matrix is defined as follows,

$$\left[F\right]=\left[\Phi\right]\cdot\left[\Omega\right]^{-1}\cdot\left[\Phi\right]^{T}=\sum_{i=1}^{N}\frac{\{\phi_i\}\cdot\{\phi_i\}^{T}}{\omega_i} \tag{8}$$

here, $\left[\Phi\right]$ is the modal matrix, and $\left[\Omega\right]$ is eigenvalue diagonal matrix, $\{\phi_i\}$ is the i^{th} modal shape vector, and ω_i is the mode circular frequency.



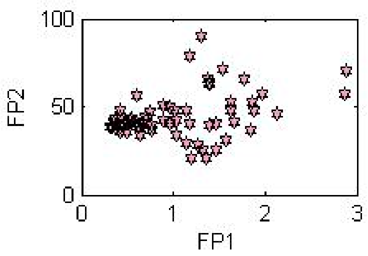
(a) Photo of the accelerate meter installed on the top panel of the girder in middle section

(b) Acceleration record

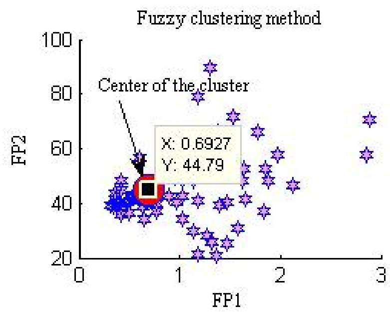
Fig. 8 The acceleration record of the vertical mode monitoring accelerometer group

Fig. 9 Scatter plot of the diagonal element modal flexibility matrix

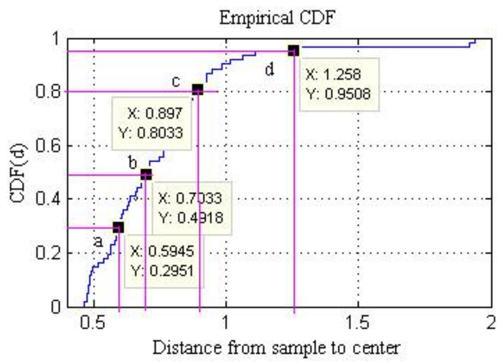
Vertical mode monitoring group contains are all together 14 accelerometers, so the dimension of the modal flexibility matrix is 14. To identify modal parameters every 30 minutes from 2 days records of 14 accelerometers, and by Eq. (8), 96 samples of the modal flexibility matrix are obtained. Theoretically speaking, all the elements in this matrix can be selected as the feature. As a matter of convenience, two diagonal elements of the modal flexibility matrix will be chosen in this paper. In order to contain the maximum information in the feature patterns, the selected pattern should be independent. Fig. 9 gives 14 scatter plots of diagonal elements in the modal flexibility matrix. The element in the i^{th} row and j^{th} column of the plot matrix gives a correlation measure between i^{th} and j^{th} the diagonal element in modal flexibility matrix. The first and fifth diagonal elements in the modal flexibility matrix are chosen to act as representative feature patterns, because the correlation coefficient ρ calculated from the 1^{th} row and 5^{th} column of the scatter plot is the smallest ($\rho=0.106$), which means that this selected feature pattern will contain the maximum bridge vertical modal information.



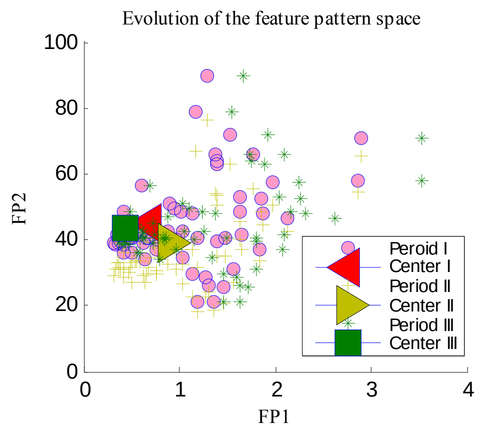
(a) The feature space tensioned by selected patterns



(b) The center found by fuzzy clustering approach



(c) The threshold determined by distance empirical cumulated density function



(d) The evolution of the cluster and its center, for long term monitoring.

Fig. 10 The fuzzy clustering algorithms for threshold system updating and evolution

Fig. 10(a) is the feature space tensioned by chosen patterns above. Fig. 10(b) is the fuzzy clustering result. The center of the data calculated from equation 6, as shown in Fig. 10(b), point (0.6927, 44.79) means that all the sample points are distributed around the center point (0.6927, 44.79). The Matlab function 'fcm' is used to find the center of the data, needing 6 iterations to obtain a convergent solution.

After clustering, the distance between each sample point (FP1, FP2) to the cluster center can be calculated. From this, two days modal flexibility matrix data, comprising 96 distance values varying from zero to a maximum of 1.94. Fig. 10(c) gives the empirical cumulative distribution function. The threshold of this feature space can be determined by the empirical probability value of the distance. In this case, the parameters 'a', 'b', 'c', and 'd' dividing the modal flexibility defined feature space are designated as 0.5945, 0.7033, 0.897, 1.258, with empirical probabilities of 30%, 50%, 80%, and 95%. The dimension of the space can be reduced to one, with some risk of the fuzzy inference system avoiding an exploding dimension. The subspace can be partitioned with intervals as [0 0.5945], [0.5945 0.7033], [0.7033 0.897], [0.897 1.258], [1.258 +∞].

Fig. 10(d) gives the illustration of evolution of the online evaluation system. Periodic updating of this system is needed. Every fixed period, the data set and its center are re-analyzed, and the empirical cumulative distribution function (CDF) are estimated again, the parameters 'a', 'b', 'c', and 'd' can be re-defined. Evolving the thresholds is the key to evolving the whole evaluation system, and the center moving tracks reflect the history of the feature space. Here, there data set representing three periods - period I, II, and III are plotted on Fig. 10(d), its corresponding center is (0.693,44.79), (0.693,34.5), and (0.729, 44.79) . In long term monitoring, this data is tracked continuously.

5. The performance of the updated online evaluation system

To validate the performance of the updated online evaluation system by the above mentioned approach, a comparative investigation was conducted before and after updating. The vertical mode monitoring group was not used as an evaluation item in the baseline period, so the cable force monitoring group was chosen for comparison. The performance of the vertical mode monitoring group will be described elsewhere.

The initial threshold of the relative cable force (defined as the distance of cable force from the designed value under dead load to the value under live load and dead load) is [200 kN, 500 kN] in level one and [500 kN, +∞] in level two, values taken from the bridge design specification. There are 25 instances of data exceeding the threshold value of 200, and 6 instances of data exceeding the threshold 500 in a month (Fig. 11). The general score of the group calculated by the FIS engine is 50.97, judged as 'Ordinary'; because the bridge is in good condition, in another words, 'health', which is inconsistent with the judgment 'Ordinary'. That is a troublesome conclusion, because it is prone to induce bridge owners' worrying about the security of the bridge. After one year of monitoring, the parameters dividing the feature space are modified according the fuzzy clustering approach described above, the center of cable force index is 67 kN, and the thresholds are 0 kN, 67 kN, 78 kN, 107 kN, 123 kN, and 306 kN, corresponding to a CDF value of 100%, 50%, 60%, 80%, 95%, and 99% (Fig. 12). To designate these thresholds (0 kN, 67 kN, 123 kN, and 306 kN) to the parameters of antecedent membership function 'a', 'b', 'c', and 'd', the parameters for FIS are then updated according to the real cable force data. Feeding this parameter into the FIS engine, the total score is 87, and the status is judged as ‘healthy’, this reflects the true cable status of the Donghai Bridge, indicating the validity of the updated online evaluation system.

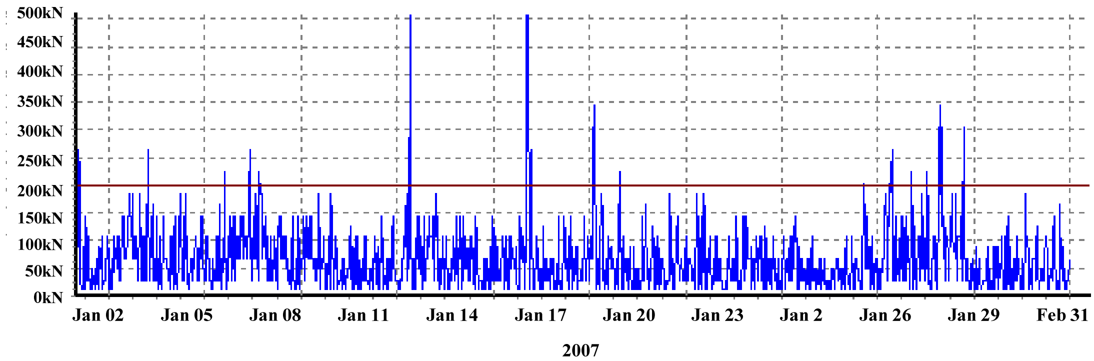


Fig. 11 Cable force index history over one month

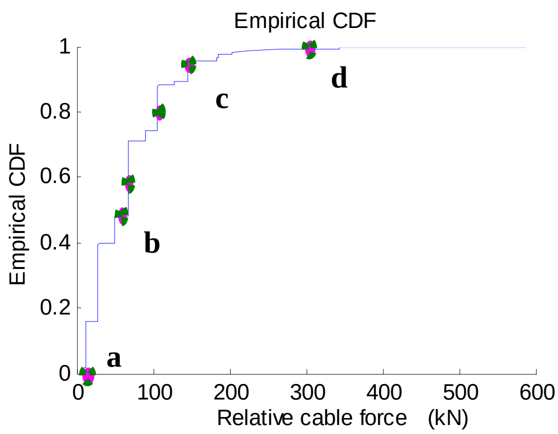


Fig. 12 The cumulative distribution function of the distance of cable force index

6. Conclusions

In this paper, the development a fuzzy inference system with an analytical hierarchy process (AHP) based online evaluation technique is described. AHP hierarchical tree architecture was introduced for graded evaluation of a complete 32-km bridge. The fuzzy inference system is applied here to successfully realize evaluation computing at the lowest level nodes of the tree-like architecture. The initial thresholds of each index are set to an initial value obtained from structural damage and performance evolution analysis of the bridge from the first year online evaluation using the DHBHMS, and is updated by actual monitoring-data based feature patterns and corresponding threshold systems. A fuzzy clustering approach helps to give a reasonable feature space division. The case study of the DHBHMS shows its validity and that the technique developed in this paper can be used to update an online FIS system in the DHBHMS. The modal parameter-based feature pattern modal flexibility matrix is an important evaluation item.

The application results show that the techniques this paper used are reasonable and reliable, fulfilling the online evaluation requirements of the Donghai Bridge Health Monitoring System and acting as a long term online evaluation system.

Acknowledgments

This paper is supported by the state high-tech research and development plans (863), Grant No. 2014AA110402, the Project of National Key Technology R&D Program in the 12th Five Year Plan of China (Grant No. 2012BAJ11B01), National Nature Science Foundation of China (Grant No. 50978196), the Fundamental Research Funds for the Central Universities, and State Meteorological Administration Special Funds of Meteorological Industry Research (Grant No. 201306102).

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