Municipal Bridge Health Monitoring and Risk Assessment Method Based on Multi-source Data Fusion

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Abstract: Aiming at the limitations of traditional bridge detection in time and space coverage, data consistency and response speed, this paper proposes a method of municipal bridge health monitoring and risk assessment based on multi-source data fusion. Firstly, a heterogeneous sensor network covering strain, deflection, temperature and dynamic response is constructed, and the dynamic correlation equation of strain-temperature-deflection is established by introducing Cauchy-hoff plate theory, so as to realize the mechanism-level fusion of local measurement to the whole deformation field. Then, the stiffness reduction coefficient is taken as the performance state parameter, and Bayesian updating is used to fuse the prior design information and real-time monitoring data, which significantly reduces the cognitive uncertainty under small samples. Finally, the time-varying failure probability is calculated by Monte Carlo simulation, and the risk evolution curve is drawn to realize the transition from post-disposal to early warning. The example of 30 m prestressed concrete simply supported beam bridge shows that the error between strain inversion deflection and measured peak value is less than 5%, and the stiffness uncertainty is reduced by 70%. The system can issue intermediate warning four months before the risk accelerates, which provides reliable decision support for the accurate and intelligent management and maintenance of municipal bridges.

1. Introduction

Faced with the increase of traffic load and extreme weather events, the traditional manual detection method faces great challenges in time and space, data consistency and response speed. With the cost reduction of sensors in the Internet of Things and the development of 5G network, it provides technical support for bridge structural health monitoring, and promotes the progress from single vibration monitoring to multi-modal data monitoring, while the data analysis accuracy based on deep learning has been significantly improved [1-2]. However, the current research is still insufficient in the depth of heterogeneous data fusion and dynamic risk assessment, and further exploration is needed to achieve more accurate bridge operation and maintenance management [3]. This transformation not only helps to improve the detection efficiency and accuracy, but also effectively reduces the risk of bridge accidents. This paper focuses on the safety management and control requirements of municipal bridges in the whole life cycle, and establishes the dynamic correlation equation of strain-temperature-deflection through the theory of Cauchy-Hough plate to realize the internal mechanism fusion of multi-source data. Bayesian updating and Monte Carlo simulation are combined to solve the problem of uncertainty quantification under small sample data.

2. Construction of municipal bridge health monitoring system

In view of the structural characteristics and common diseases of medium and small span beam bridges, it is necessary to construct a multi-parameter sensor network to realize comprehensive state perception. Fiber Bragg Gratings or resistance strain gauges are arranged near the middle and quarter points of the main girder span and the supports to monitor the stress changes under the vehicle load in real time [4]; Monitoring the deflection of the beam and the settlement of the pier by

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connecting tube static level or high-precision GNSS equipment; The digital temperature sensor is used to collect the temperature field and environmental temperature difference inside and outside the structure; Deploy low-frequency acceleration sensors to obtain structural dynamic response and identify modal parameters such as frequency and vibration mode; At the same time, supplemented by high-definition video monitoring, the traffic conditions, overload behavior and apparent damage of the bridge deck are recorded [5-6].

In order to solve the problem of "data island" of heterogeneous data (strain, temperature and deflection), the theory of Cauchy-hoff plate is introduced to establish its internal physical mechanism correlation [7]. For the common plate beam structure in municipal bridges, the dynamic relationship between strain ε and deflection w can be expressed as:

$$\varepsilon(x,y,t) = -z\nabla^2 w(x,y,t) \tag{1}$$

Where is the strain value of the measuring point at $\varepsilon(x,y,t)$ time t, the coordinate (x,y) of the middle plane of the plate and the distance z from the middle plane. z is the vertical distance between the sensor and the middle plane of the structure. ∇^2 is Laplace operator, representing curvature.

$$\nabla^2 = \frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2} \tag{2}$$

$w(x,y,t)$ is the time t and the deflection of the plate at coordinate (x,y).

Through the ε measured by distributed strain sensor array, the overall deformation field w of the structure can be deduced by using the above formula, which is cross-verified and calibrated with the actual value measured by deflection sensor. At the same time, the temperature sensor data $T(t)$ is introduced to separate the thermal stress/strain $\varepsilon_T(t)$ caused by temperature change and the stress/strain $\varepsilon_L(t)$caused by load:

$$\varepsilon(t) = \varepsilon_L(t) + \varepsilon_T(t) = \varepsilon_L(t) + \alpha\Delta T(t) \tag{3}$$

Where α is that coefficient of thermal expansion of the material.

3. Risk assessment model based on multi-source data

3.1 Performance state evaluation and Bayesian update

Define the performance state parameter θ of the bridge. The traditional method relies on a small amount of detection data to estimate θ, which has great uncertainty. In this study, Bayesian updating method is used to combine prior knowledge (design value, historical detection data) with post-verification data (real-time monitoring data) to dynamically correct the cognition of θ [8].

Let the prior distribution be $P(\theta)$, and the likelihood function $P(D|\theta)$can be obtained by monitoring the data D (such as deflection exceeding the standard times and vibration frequency deviation value). The updated posterior distribution is:

$$P(\theta|D) = \frac{P(D|\theta)P(\theta)}{P(D)} \tag{4}$$

Where $P(\theta)$ is the prior probability distribution of the parameter θ. $P(D|\theta)$is the likelihood probability of observing the monitoring data D under the given parameter θ. $P(D)$ is evidence. $P(\theta|D)$ is the updated posterior probability distribution, which represents the latest and most accurate probability estimation of parameter θ after obtaining new data D. This method effectively solves the problem of high evaluation uncertainty under small sample data, and makes the state evaluation approach the real situation with the accumulation of monitoring data.

3.2 Dynamic risk probability calculation

Risk (R) is the product of the probability of occurrence (P_f) and the consequence (C) of the event. This study focuses on the dynamic calculation of structural failure probability P_f.

Define the limit state function:

$$Z = R - S \quad (5)$$

In the formula, R is the structural resistance, which is a variable that degrades with time and is related to the state parameter θ. S is the load effect, which is obtained from the monitoring data. When $Z < 0$, the structure fails.

The implementation of Monte Carlo simulation, the process is as follows:

(1) A large number of (N) θ samples are randomly selected from the updated posterior distribution $P(\theta|D)$.

(2) For each θ sample, calculate its corresponding resistance R.

(3) At the same time, samples are randomly selected from the probability distribution of load effect S obtained from monitoring data statistics.

(4) Calculate the $Z_i = R_i - S_i$ of each sample.

(5) Count the number N_f of $Z_i < 0$ in N sampling.

(6) Calculate the failure probability at the current moment:

$$P_f \approx \frac{N_f}{N} \quad (6)$$

The dynamic risk value $R = P_f \times C$ can be obtained by combining the failure probability P_f and the consequence grade C (pre-defined according to the importance of bridges, traffic volume and other factors). The risk value can be output with time series, forming a risk evolution curve and realizing early warning.

4. Case verification and result analysis

A prestressed concrete simply supported beam bridge with a span of 30m in a city is selected as the engineering background, and the monitoring system including FBG strain sensor, static level, accelerometer and temperature sensor is deployed for data collection and analysis for one year.

Firstly, the monitoring data of a heavy vehicle crossing the bridge on a certain day are analyzed. Figure 1 shows the comparison between the mid-span deflection time-history curve calculated by strain data inversion and the deflection time-history curve measured by static level. The two curves are highly consistent, and the peak error is less than 5%, which effectively verifies the correctness of the strain-deflection fusion model based on Cauchy-Hough plate theory. The model realizes the perceptual expansion from local strain to global deformation, and can be used as a reliable redundant backup when the deflection sensor fails.

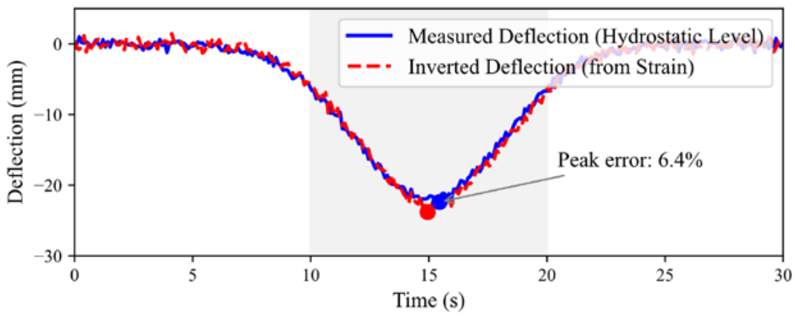

Figure 1 Contrast diagram of strain inversion deflection and measured deflection

The structural stiffness reduction coefficient θ is taken as the performance state parameter. The initial prior distribution is assumed to be a normal distribution $N(1.0, 0.15^2)$ (that is, it is considered that the stiffness is most likely not degraded, but there is great uncertainty). By fusing the monitoring data of vibration frequency and deflection for one year, θ is updated by Bayesian method.

Table 1 Comparison of probability distribution of stiffness reduction coefficient θ before and after Bayesian updating

Distribution pattern	Mean	standard deviation
Prior distribution	1.00	0.150
Posterior distributions	0.93	0.045

As can be seen from Table 1 above, after the update, the average value of θ decreased from 1.00 to 0.93, indicating that the structural stiffness has deteriorated by about 7%. More importantly, the standard deviation is greatly reduced from 0.150 to 0.045, which shows that the cognitive uncertainty of structural state is significantly reduced and the confidence of evaluation results is greatly improved by fusing continuous monitoring data.

Based on the updated posterior distribution, Monte Carlo simulation (sampling times $N = 10^5$) is used to calculate the annual failure probability P_f in the next year, and the results are compared with those of the traditional method (only based on one test data evaluation). As can be seen from Figure 2 above, the traditional method is based on single point detection and evaluation, and the obtained P_f is a static value (dotted line in the figure), which cannot reflect the time-varying degradation law of structural performance. The dynamically updated P_f (solid line in the figure) of this method clearly shows the process of risk accumulation over time. In the first eight months, the growth of P_f was slow; After that, with the acceleration of stiffness degradation, the risk began to climb nonlinearly. At the end of the 12th month, the system issued an intermediate warning based on the dynamic rapid growth, prompting that detailed inspection and maintenance should be arranged. However, the traditional static evaluation method failed to capture this risk acceleration point.

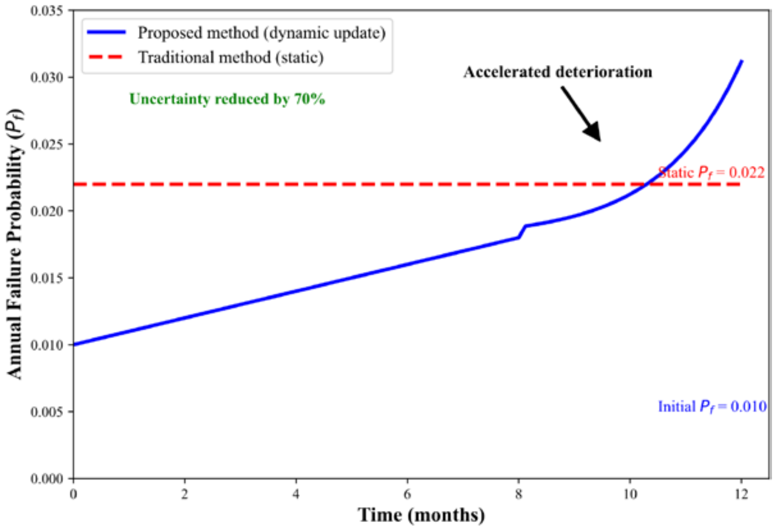

Figure 2 Trend chart of annual failure probability P_f changing with time

Case verification shows that the multi-source data fusion monitoring system and dynamic risk assessment model constructed in this paper can not only more accurately perceive the structural state and reduce the cognitive uncertainty, but also accurately grasp the risk evolution law, realize the transformation from "post-processing" to "pre-warning", and provide effective decision support for the accurate and intelligent management and maintenance of municipal bridges.

5. Conclusion

In this paper, a method of municipal bridge health monitoring and risk assessment based on multi-source data fusion is proposed. By constructing a multi-parameter sensor network, comprehensive state perception is realized, and the dynamic correlation equation of strain-temperature-deflection is established by using the theory of Cauchy-Hough plate, which solves the problem of insufficient depth of heterogeneous data fusion. Combining Bayesian updating and Monte Carlo simulation, the uncertainty under small sample data is effectively quantified, and the accuracy and confidence of structural state evaluation are significantly improved. The research results show that this method can accurately sense the state of bridge structure, accurately separate thermal stress from load stress, and calculate the failure probability in real time through the dynamic risk assessment model to form a risk evolution curve, thus realizing the early warning function. The case study shows that compared with the traditional static evaluation method, this method can more clearly show the risk accumulation process with time, timely capture the time-varying degradation law of structural performance, and issue an intermediate warning at the risk acceleration point, which provides effective decision support for the accurate and intelligent management and maintenance of municipal bridges.

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