Engineering 25 (2023) 194–203

Contents lists available at ScienceDirect

Engineering

journal homepage: www.elsevier.com/locate/eng

Research
Structure Health Monitoring—Review

Intelligent Monitoring System Based on Spatio–Temporal Data for Underground Space Infrastructure

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ARTICLE INFO

Article history:
Received 19 December 2021
Revised 7 July 2022
Accepted 10 July 2022
Available online 13 September 2022

Keywords:
Structure health monitoring
Underground space infrastructure
Machine learning
Spatio–temporal data

ABSTRACT

Intelligent sensing, mechanism understanding, and the deterioration forecasting based on spatio–temporal big data not only promote the safety of the infrastructure but also indicate the basic theory and key technology for the infrastructure construction to turn to intelligentization. The advancement of underground space utilization has led to the development of three characteristics (deep, big, and clustered) that help shape a tridimensional urban layout. However, compared to buildings and bridges overground, the diseases and degradation that occur underground are more insidious and difficult to identify. Numerous challenges during the construction and service periods remain. To address this gap, this paper summarizes the existing methods and evaluates their strong points and weak points based on real-world space safety management. The key scientific issues, as well as solutions, are discussed in a unified intelligent monitoring system.

1. Background

The rapid growth of the economy has increased the need for the utilization and development of underground space. The beginning of the underground infrastructures in China could be dated to 1990, although this effort was mostly concentrated on subway transportation and underground parking lots. With the improvement of urbanization, urban underground space development began to speed up. Since 2016, the area of underground space has expanded to 844 million square meters, and China currently has the largest underground space in the world. For example, the under-construction Beiheng Passage Project in Shanghai is a combination of the subway station, railway station, and supermarket. The area operates in a multiple-function manner, and the comprehensive design has become the main trend for underground infrastructure. In addition, the maximum depth of the Beiheng Passage Project could reach 48 m. This depth indicates the project is a multi-level and tridimensional structure. In summary, the main characteristics of the underground infrastructure are deep, big, and clustered.

Compared to other types that afflict buildings and bridges, disease and deterioration in underground structures are more difficult to locate. First, service checking and maintenance are restricted by the space. Second, the complex situation underground makes it challenging to recognize diseases and address emergencies. Diseases in this context can be divided into three main categories: progressive diseases, sudden disasters, and natural disasters. For progressive diseases, due to complex urban geological conditions, most of the riverside and coastal cities are built upon soft soil with severe ground subsidence. Along with the construction and external load disturbances, progressive diseases of urban underground spaces occur frequently, which reduces their service life. For sudden disasters, such as explosions, fires, and traffic accidents, the accident chain is difficult to determine, which increases the structural damage and deterioration of the infrastructure. Finally, natural disasters, such as typhoons, rainstorms, and earthquakes, could easily destroy the structure. Due to space limitations, it is difficult for the damage to be discovered in a timely way and be assessed accurately, and these kinds of disasters always result in the loss of life and property.

2. Problems with the current underground infrastructure

The main characteristics of underground infrastructure make it difficult to recognize and give early warnings for damage. However, enormous losses result once those damages occur. Thus, the

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https://doi.org/10.1016/j.eng.2022.07.016
2095-8099/

construction and service safety of underground space structures are major issues that need to be resolved. Although the technology of underground infrastructures is developing rapidly, the current sensing and modeling methods cannot ensure the safety of the infrastructure or individuals associated with it. The gaps between the technology and real-world needs are still significant in terms of in state sensing, patterns and damage understanding, and future state forecasting.

2.1. Low data quality

Sensing techniques have adopted automatic equipment instead of manual methods. Checking the state via manual percussion and visual inspection is inconvenient and consumes too much manpower. In an Internet of Things (IoT) environment, deploying large-scale monitoring sensors helps to collect multiple types of data to form a big data environment. These data include the state of the infrastructure and some important information such as the deformation, temperature, and inner damage of structures. However, most of the monitoring systems are built upon fiber sensor networks, radar, and laser devices, which monitor the state of the infrastructure by acoustics and optics. Most of them only record a single type of performance metric and suffer from the transmission delays and the difficulty operating in the extreme environment, which causes the quality of multiple types of data to vary. Being unable to obtain a complete and reliable perspective for the whole infrastructure could lead to mistakes in the state evaluation and dynamic modeling. The data quality of sensing needs to be improved.

2.2. Latent disease feature

Some types of damage and diseases could be discovered via the analysis of the raw monitoring data. Classifying the data collected by the single type sensors via the human-designed threshold, the maintainers could judge whether the emergency has happened. However, in the complicated underground space, diseases and damage could occur in inconspicuous places, even places not covered by monitoring sensors. Additionally, affected by some extreme environments, the formalization of diseases could be contributed by multiple factors, which creates significant difficulty for the mechanism analysis and tracing of the leading source. The lack of systematic and scientific structural catastrophes in early warning theory and safety information management methods makes it difficult to trace the source of underground space structural diseases and obtain the state of the infrastructure. To capture more reliable warning signals and abnormal features, anomaly detection technology has to be improved.

2.3. Dramatic changing state

Analysis of the formation of diseases helps to detect and determine anomalies. Moreover, it contributes to early warnings for the coming damage and leaves enough time for the authorities to manage the problem. In this process, forecasting plays a vital role. Statistical analysis methods calculate the correlations between the target time step with the history or employ the autoregressive integrated moving average model (ARIMA). The relatively low representation and modeling ability make it difficult to extract the hidden patterns in a complicated underground space environment. By applying the actual boundary conditions, the numerical simulation models [1,2], such as the finite element method (FEM) and discrete element method (DEM), calculate the weak positions of the structure, which is reflected by the numerical results. However, this might require plentiful field investigation results and highly complex models [3,4]. In addition, it is invalid to employ the original boundary conditions when emergencies occur. Under the rapid evolution of the states and untimely collapse and cracking, whether the emergency or the slow deterioration is hard to capture the main factors due to the messy cause. Thus, accurate and reliable forecasting methods for future states are needed. Finally, a complete system consists of the intelligent diagnosis, accurate predictions of deterioration trends, and dynamic early warnings of an underground space structure disease or disaster.

3. Solutions

In recent years, computer science has been applied to domains such as transportation planning, recommendation systems, and natural language processing, which offers a new perspective for maintaining the safety of infrastructures. Compared with these domains, underground infrastructure has a lower data quality. The hidden disease patterns and changeable tendencies also prevent the extraction of the true factors. To address the above problems, we examined four topics: ① a unified underground space infrastructure monitoring system based on spatio–temporal big data analysis; ② real-time information sensing based on light feature space construction; ③ anomaly detection based on hidden pattern understanding; and ④ future tendency forecasting based on spatio–temporal correlations modeling. Table 1 [5–94] offers a summary of the following parts.

4. Framework of spatio–temporal underground infrastructure monitoring system

In this section, we discuss the framework of the intelligent monitoring system shown in Fig. 1. The basis of the system is made up of the data collected by the monitoring sensors and external factors such as structure, environment, and risk category. Multiple kinds of raw data are arranged in a structured shape, such as time series, spatio–temporal data, and graph data. The analysis of engineering big data reveals the mechanism of the diseases and discovers the knowledge from two perspectives: domain knowledge-based methods and data-driven methods. Research on the three problems plays a vital role in this intelligent monitoring domain. First, the problems of lost data and the limitation of the sensors' location all result in low data quality. However, sensing the environment of the structure and offering a digital description lay the foundation for later analysis. Spatial inference for the whole

Table 1
Research approach and related work summary.

Goal	Existing problem	Solutions
Holographic sensing	Low data quality	Data augmentation based on feature compression [5–17] Response reconstruction based on heterogeneous data fusion [18–41]
State understanding	Latent disease feature	Anomaly detection based on clustering methods [42–50] Disease diagnosis based on multi-view analysis [51–70]
Degradation forecasting	Multiple affect factors	Spatial correlation modeling based on graph neural network [71–74] Temporal dependency extraction based on external factors [75–94]

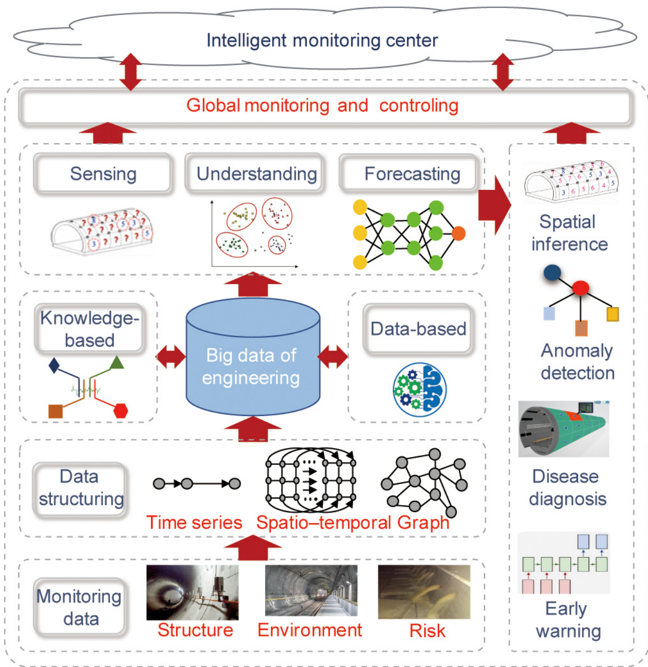

Fig. 1. The framework of the intelligent monitoring system.

structure could offer a complete view. Second, some damage and diseases on the structure do not emerge immediately. Understanding the mechanism behind and capturing the hidden representations helps to discover anomalies and damage, which offers the safety diagnosis and state evaluation for the structure. Lastly, with the complete historical data and the current state of the structure, forecasting the future tendency and dynamic equips the system with the early warming ability. The advanced reaction minimizes the losses and protects life safety. By digging into the three problems above, a unified intelligent monitoring system is built. The combination of sensing, understanding, and forecasting governs the infrastructure comprehensively. The global center receives heterogeneous information and offers strategies to prevent the diseases and obtain a longer service period.

5. Holographic sensing based on feature compression

Advancements in sensor technology allow for a large number of collected data to show the infrastructure's state from several different perspectives. However, it is challenging to incorporate multiple types of data. First, the lost data problem hinders the development and application of wireless sensor technology for structure health monitoring; it is common in real-world scenarios and impossible to remove. Second, the format of the data varies. Different sample frequencies, phases, and time lengths all cause challenges for the state sensing. Third, redundant information accounts for the majority of the data. The high cost of storage and computation leads to a low monitoring efficiency and late state sensing. Thus, real-time information sensing based on the light feature space construction is needed. By taking the physical space information as input, the tensor decomposition and auto-encoder can extract deep hidden features from the massive heterogeneous monitoring data. The orthometric base features could be fused with the statistical analysis. Using feature augmentation methods for underground space infrastructure, the large-scale feature sets are obtained, and the correlations could be evaluated. Moreover, within informative base features, the physical space could be reconstructed as digital, which helps to reveal the complete infrastructure states. The framework is shown in Fig. 2.

5.1. Data augmentation

Widely developed wireless sensor technology provides the similar functionality of traditional wired systems with a much lower installed cost, which results in the explosive increase of collected data. However, the lost data problem hinders the development and application of wireless sensor technology of structure health monitoring. The causes of missing data vary, such as radio interaction, transmission error, sensor fault, and power supply interruption, which all harm the data collection process to a certain extent. It is impossible to remove this influence and tackle the problem at its root.

Many efforts have been made in this domain. Some research that proposed to utilize the numerical simulation models to solve the lost data problem can be divided into model-based categories, which requires field investigations and highly complex models [5,6]. In addition, it is invalid to employ the initial boundary conditions when emergencies occur. To overcome the above problem, data imputation based on machine learning methods has been widely adopted, and most of these methods reconstruct the data by the correlations between sensors [7–9]. Bao et al. [10] proposed a novel compressive sampling method to impute the missing values, which the monitoring sensors collected from a bridge structure. Huang et al. [11,12] utilized the intra-correlation between sensors and the inter-correlation between strain data and temperature values to recover the missing values. The spatial correlation of different strain sensors was extracted to interpolate the missing stress measurements [13]. This work also pointed out that the ratio of lost data should not be more than 30 %. Chen et al. [14] made a real-time augmentation with multi-sourced urban data. It is worth mentioning that Tan et al. [15] employed non-matrix factorization to extract the correlations between multiple sensors with the low-rank assumption, and used the end-to-end stochastic gradient descent framework to obtain an excellent result. They filled in the missing values for one sensor at a time. If the number of anomalous sensors is more than one, this problem can be solved by conducting the filling process repeatedly. The recovery process is defined as follows:

$$X \approx UV^{\mathrm{T}} \quad \hat{X} = UV^{\mathrm{T}} \tag{1}$$

where X represents the monitoring data, and U and V are the low-rank matrices. With the rapid development of artificial intelligence technology in computer science, some deep neural networks were introduced to deal with complex and non-linear correlations. Fan et al. [16] recovered the dynamic acceleration data by convolutional neural network (CNN). Jiang et al. [17] made the data imputation with the incomplete dataset by the generative adversarial network, which resulted in a remarkable improvement compared with the conventional imputation method. With the development of wireless sensor networks for long-term monitoring, more data will be collected per day. Deep learning methods are a potential future direction for lost data imputation.

5.2. Response reconstruction

Valid monitoring data provide foundations for mechanical behavior analysis. We discussed how to ensure the data quality in the last subsection. However, although the locations where the monitoring sensors are installed are carefully selected, the number of sensors is much smaller than the total number of degrees of freedom (DOFs) of the structure due to the limitation

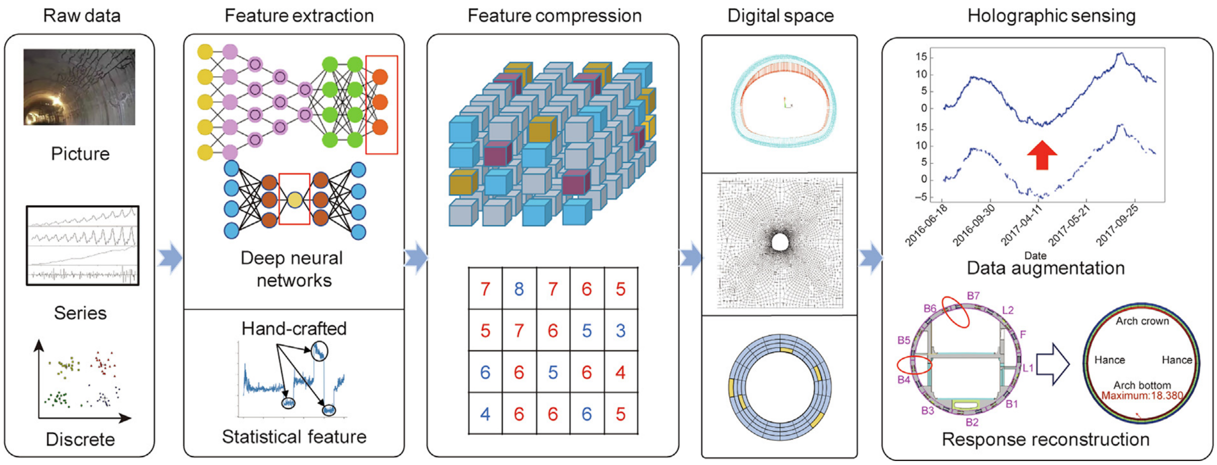

Fig. 2. Holographic sensing with feature compression.

of the budget and the inaccessibility of some locations for measurement operations [18]. However, data at locations where no monitor sensors exist are always useful and sometimes critical. To address the excessive volume of data and the limitation of the sensor arrangement, some efforts have been made in response reconstruction. The response reconstruction methods fall into two categories: model-based methods and data-based methods. The former one mainly is based on the transmissibility concept, which reconstructs the response by a transformation matrix of the function. Those methods are formulated in the time domain [19,20], frequency domain [21,22], or wavelet domain [23–25]. The Kalman filter, a well-known state estimator providing the unbiased minimum variance state estimation by combining the structural model and instantaneous measurement information, was introduced to this field based on optimal multi-type sensors placement [26–28].

Unlike the model-based methods that are limited by their modeling capacity of recovery under complex, dynamically changing environmental and operational conditions, data-driven methods are mainly used to reconstruct the short-term continuous lost data. Bao et al. [29,30] proposed the compressive sensing technique to recover and estimate the lost signals in wireless systems. Wan and Ni [31] introduced the Bayesian multi-task learning framework to reconstruct the lost temperature data and acceleration signals. Principal component analysis (PCA), singular value decomposition (SVD), and auto-encoder (AE) are widely adopted unsupervised machine learning methods that follow the information compression and reconstruction workflow [32–35]. It is worth mentioning that Tan et al. [36] not only employed a non-negative factorization method but also bridged the mechanical analysis and data-driven reconstruction. The framework is shown in Fig. 3. They used an undersea tunnel structure as an example, which is formulated as a matrix with I rows and J columns.

Due to the continuum body of the tunnel structure, the force has similar mechanical behaviors on the adjacent tunnel face area, which leads to a constraint condition to the spatial deduction training. However, the continuous similarity is not the same in all tunnel faces. For example, the force similarity in the arch crown is different from the similarity in the hance. To address this problem and bridge the mechanical analysis and data-driven deduction, the force distribution is employed to optimize the training process of the non-negative matrix factorization (NMF). Furthermore, the axial symmetry property of the tunnel structure could also be utilized. With two constraint terms, the loss function L of the spatial deduction is defined as follows:

$$\begin{aligned} L(U,V,\mu_1,\mu_2) = & \sum_{(i,j)\in\mathbb{A}} \| X_{i,j} - U_{i,:}\cdot V^{\mathrm{T}}_{:,j} \|^2 \\ & +\mu_1 \sum_{i=1}^{I}\sum_{j=1}^{J} Y_{i,j} \| U_{i,:}\cdot V^{\mathrm{T}}_{:,j} - U_{i,:}\cdot V^{\mathrm{T}}_{:,j+1} \|^2 \\ & +\mu_2 \sum_{i=1}^{I}\sum_{j=1}^{J} Y_{i,j} \| U_{i,:}\cdot V^{\mathrm{T}}_{:,j} - U_{i,:}\cdot V^{\mathrm{T}}_{:,J+1-j} \|^2 \end{aligned} \tag{2}$$

$$Y_{i,j} = 1 - \frac{\max(|F_{i,j}|,|F_{i,j+1}|) - \min(|F_{i,j}|,|F_{i,j+1}|)}{\max(|F_{i,j}|,|F_{i,j+1}|)} \tag{3}$$

where F is the force. $\mathbb{A}$ is the set of non-empty units. $Y_{i,j} \in (0,1)$ is the similarity measured by force analysis, and the larger value of $Y_{i,j}$ indicates the closer relationship of points i and j. μ_1 and μ_2 are hyper-parameters to balance the values of two constraints terms. $U_{i,:}$ and $V_{:,j}$ indicate the ith row of U and jth column of V. I and J is the total number of i and j, respectively. The reconstruction result is shown in Fig. 4. The circular ring in the left represents the model of a tunnel. The colored grids indicate the locations with sensors, and the white grids means that there are no monitor sensors. The deeper color indicates the bigger stress. After the spatial deduction, the states all tunnel faces are inferred, and the historical values could also be obtained.

Recently, with the rapid growth of computer science and the volume of data, some deep learning methods have attracted much attention for their capability in dealing with massive amounts of data and the end-to-end training framework. Some artificial neural networks (ANNs) [37,38] and CNNs [39,40] are widely used to reconstruct the response. Jiang et al. [41] employed the sequence-to-sequence architecture cooperating with the attention mechanism, and the experiment results were satisfactory, which offers a new perspective for response reconstruction.

6. Anomaly detection based on hidden pattern understanding

Compared with traditional finite element-based analysis methods, the data-driven identification methods are less likely to be affected by changes in the external environment, which leads to the more accurate identification of the micro-damages and hidden defects in underground space structures. Therefore, we can evaluate the correlation of the structural behavior from different perspectives and build a feature set of early micro-damages via metric learning and non-linear feature extraction. The method with adaptive abnormal-behavior discovering capabilities could

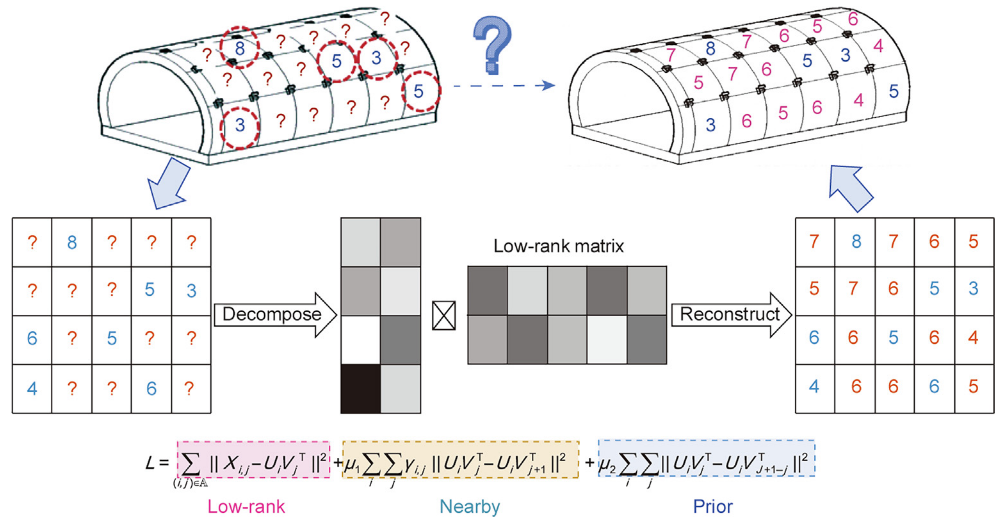

Fig. 3. The framework of response reconstruction with domain knowledge (the variables are defined below).

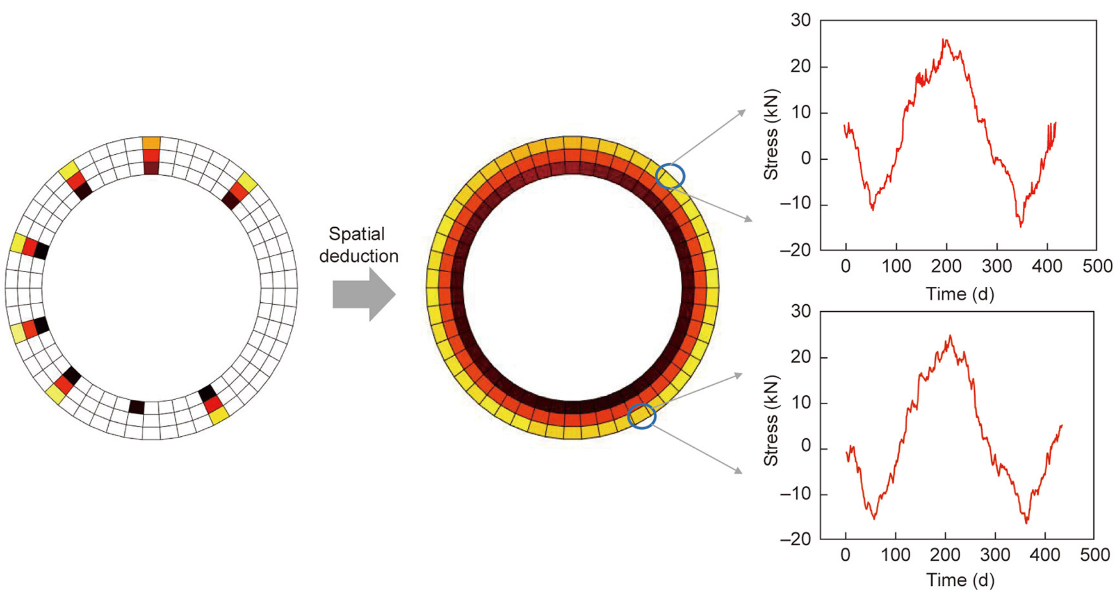

Fig. 4. The spatial inference in a real case.

be developed by in-depth data mining and feature extraction. Using the dimension reduction analysis of the source data, the problem of the few-shot abnormal data samples and hidden abnormal features is solved by obtaining the different bases of the disease. Additionally, it contributes to the intelligent identification of hidden defects and early micro-damage of the urban underground space structure. The framework is shown in Fig. 5.

6.1. Anomaly detection

In terms of data transmission, the wireless system data collection quality is influenced by numerous external factors such as the humidity, electromagnetic field environment, temperature, and transmission power. Additionally, the data acquisition process is subject to failures led by transmission errors. Abnormal monitoring data cause difficulties for the state analysis, while the incomplete information cannot give an accurate evaluation of the current status. Recently, Bao et al. [42] and Tang et al. [43] examined data anomalies in terms of the vision perspective. They drew pictures of the dynamic strain response to show the state of the structure. They introduced the technology in computer vision and cooperated to use deep neural networks, such as CNNs and fully connected neural networks, to recognize the different patterns of sensors. However, the precise information contained in the raw time-series data would be dropped to a certain extent in the process of transforming the picture. Chen et al. [44] detected the anomalous trajectory online with iBOAT. These types of problems are often handled in a data-driven method, most of which follows a decomposition–reconstruction manner. Spectral analysis techniques, such as SVD [45], PCA [46,47], and wavelet analysis [48,49] are widely adopted. NMF decomposes the original matrix into two small non-negative matrices. The novel data reconstruction method compresses the data to the lower dimension space to extract hidden correlations. The element-wise distance between the original data X and the reconstructed data U, V determines whether it is anomalous, which is defined as follows:

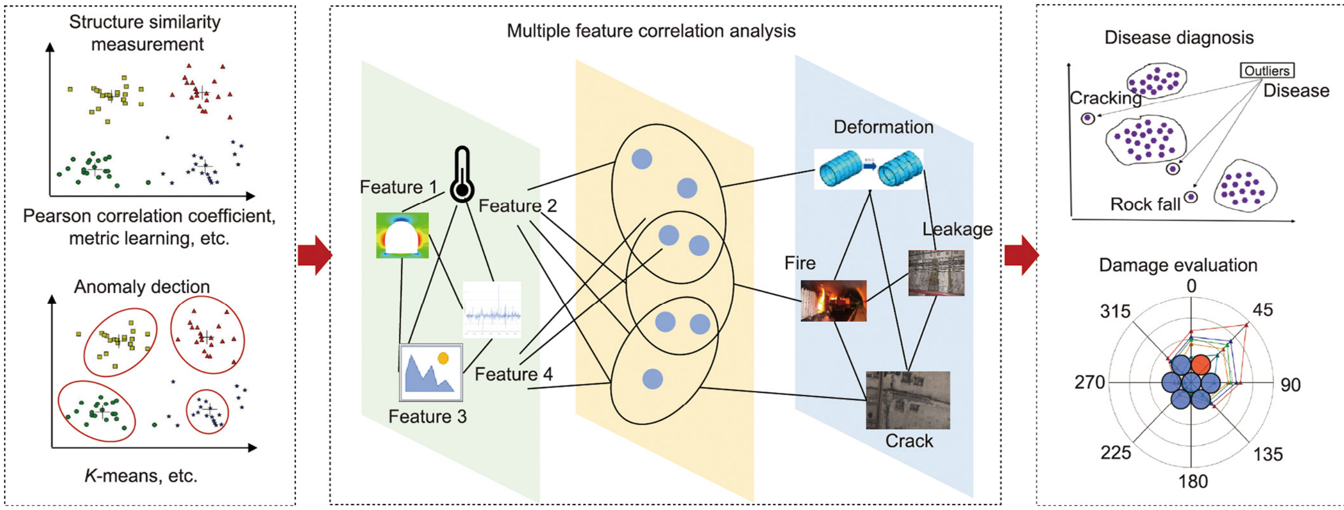

Fig. 5. Anomaly detection based on hidden pattern understanding.

$$\xi = \vartheta\left(\epsilon - \left\|X - UV^{\mathrm{T}}\right\|\right) \quad (4)$$

where ϵ is the threshold value that divides the data into normal and abnormal. Numerous adjustments and searches are performed to determine the threshold. ξ is the output. $\vartheta(\cdot)$ is a mapping function which maps the negative values to 0, and non-negative values to 1. The process described is training with the stochastic gradient descent in an end-to-end manner. The main intention in this domain is to obtain the common patterns hidden in the data. The generative adversarial network (GAN) is a novel machine learning method made up of two components, a generator and a discriminator. During the competition between the two modules, the generator gradually obtains the common patterns of the normal data [50] while it intends to cheat the discriminator. The GAN-based methods offer a new perspective and solution.

6.2. Damage assessment

A primary research area in structure health monitoring is damage localization and assessment. Reliably locating damage and forecasting its tendency are important for protecting the safety of the structure. There have been many studies on the structural damage assessment. This problem was explored using physics-based [51–53] and data-driven-based methods [54]. The natural frequency, mode, curvature, and vibratory characteristics play a vital role in the former type of methods. The analytical models are used with simulations for calibration to obtain the physical characteristics and structural current states. However, the rapidly growing data volume poses a challenge for physical-based methods. Additionally, determining the physical model could be rather difficult, as the quality of data could vary and strongly influencing. Differently, the data-driven methods discover the hidden correlations and sensitive features to assess the structural conditions. Numerous statistical approaches were employed, such as the state-space model [55,56], the auto-regressive model [57–59], and the ANN [60,61]. The Mahalanobis distance was employed to detect the outliers [62]. A fuzzy-logic model was established to build correlations between maximum acceleration amplitudes with nominal train speeds [63]. Clustering is also a popular unsupervised learning method, which can discover abnormal data according to the outliers [64,65]. Liu and Ni [66] assumed a Gaussian distribution for the normalized rail bending strain. Recently, some deep learning methods, such as one-dimentional (1D) CNN and DNN, were introduced to deal with the insufficiency of statistical methods' ability to capture the non-linear correlation [67,68]. However, these solutions do not improve the problem formulation or capture the high-level feature correlations of the monitoring data and the damage. The correlations between multiple kinds of monitoring data are still unknown. With a feature combination and selection, the hidden pattern and information could be shared and transferred properly in this domain. In this way, the deep multi-task learning framework explores the information sharing mechanism in the inputs and outputs [69,70], which provides a new perspective to solve the real-world problem.

7. Future tendency forecasting based on spatio–temporal modeling

Although the linear regression methods can calculate the correlation between the degradation behavior and the respective variables by the least square method, the univariate forecasting manner makes them ignore key information, such as the relationship among the different sensors. The features contained in the real-time monitoring data can reflect the deterioration trend of the structure accurately. The rapidly developing spatio–temporal neural network is suitable for establishing timing dependency. The popular recurrent neural network could eliminate the effect of gradient disappearance caused by the excessively long sequence by continuously obtaining the long-short-term relationship. Moreover, the multivariate time series could be formed in a graph theory manner. By constructing the adaptive adjacency matrix and automatically optimizing it in the training process, the non-Euclidean correlations are measured appropriately. Thus, the long-term degradation trend of the underground space structure can be accurately predicted. The framework is shown in Fig. 6.

7.1. Spatial dependency extraction

Exploring the spatial correlations between multiple monitoring sensors is a new domain for capturing the dynamics of a time series. In the underground space, whether the sensors are located in the same infrastructure or whether the sensors are monitoring the same mechanical property, the spatial correlation can be calculated with an optimization process or defined in a handcrafted manner. CNNs are widely used in computer vision [71,72]. CNN processes the relationship between neighbors through the

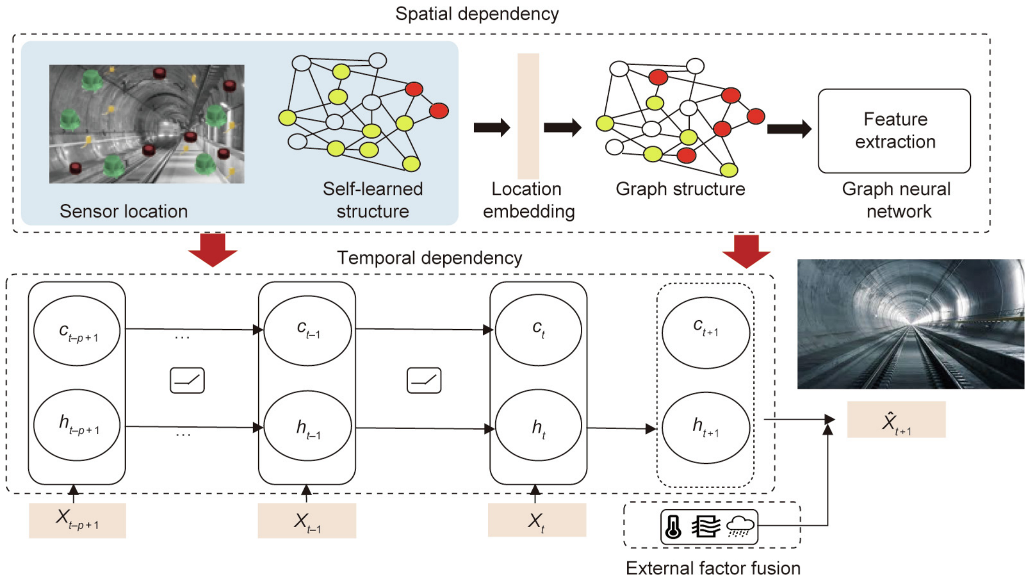

Fig. 6. Future tendency forecasting based on spatio–temporal data. X is the monitoring data; t indicates the time step, and p is the historical length; c_t and h_t represent the hidden states.

convolution kernel. Since the convolution kernel shares parameters globally, it can extract the features in the entire picture. For example, whether a face appears in the upper left corner or the lower right corner of the picture, the same feature will be obtained after the picture is processed by the same CNN convolution kernel. If modeling the structure underground is done precisely, the correlation between sensors can be extracted by the CNN. However, the locations without sensors create a problem for the hidden pattern capturing. To address this problem, a graph neural network, a generalization of the CNN, is fit to deal with non-Euclidean data naturally, and is defined as follows:

$$X\bigstar_G g_\theta = \sum_{i=0}^{K}\left(\hat{A}\right)^i X\theta_i \tag{5}$$

where X denotes the input value, and $\bigstar_G$ represents the convolution operation on the graph $G = (v, \varepsilon)$, where v and ε are the set of nodes and edges, respectively. g_θ is the parameters, K indicates the number of diffusion processes, and $\hat{A}$ indicates the normalized adjacency matrix. Taking the random walk normalization as an example, given the adjacency matrix as A, $\hat{A} = D^{-1}A$ where $D_{ii} = \sum_j A_{ij}$. In the traffic prediction domain, the adjacency matrix, which is used to indicate the topological correlation, is determined by the distance between sensors [73,74]. However, the human-designed adjacency matrix could not describe the genuine relations properly. To address this problem in the structure health monitoring domain, for each sensor, we construct the adaptive adjacency matrix, which is optimized during the training process:

$$A = \mathrm{softmax}\left(\mathrm{ReLU}\left(E_1 E_2^{\mathrm{T}}\right)\right) \tag{6}$$

where the E_1 and E_2 are the representations for each sensor. Although the adaptive adjacency matrix can draw the spatial correlations automatically, there are still some problems, such as the hierarchical spatial correlation extraction and the evolving dependency modeling, which remains to be the future direction.

7.2. Modeling temporal dependency with external factors

Much effort has been made in the time series forecasting domain. Predicting the variation of the structural stress with time from a recorded time series is a common target for structural condition monitoring and assessment, and auto-regression (AR) and its variants have been widely applied in this regard [75]. Singular spectrum analysis (SSA) decomposes and reconstructs the trajectory matrix obtained from the time series, and extracts signals representing different components [76]. Bayesian-based forecasting methods are powerful for modeling nonlinear dynamic systems. The abilities to update the model without reconstructing itself and accommodating both stationary and non-stationary temporal dependency render them favorably suitable for predicting the strain response [77–81]. The Gaussian process denotes the variables are subject to a normal distribution, and it is widely used in the structural states forecasting [82–86]. Some hybrid approaches take the seasonal influence and short-term trend into consideration to capture the hidden representations precisely [87,88]. Recently, under the trend of informationizing and intelligentizing, some deep learning methods are adopted to deal with non-linear correlations. Apart from the fully connected network optimized with backpropagation [89–92], several advanced models utilizing a deep neural network framework have a more powerful ability to process time series problems. Recurrent neural network (RNN) is a deep learning model that employs sequence data as input and extracts series dependence. The hidden layer is used to preserve the information passed from previous inputs, which is defined as follows:

$$h_t = \phi(w[x_t, h_{t-1}] + b) \tag{7}$$

where x_t represents the input of time step t, and the hidden state which preserves the previous information is h_t. ϕ represents the activation function. w and b are the parameters and biases, respectively.

In time series problems, the basic RNN suffers from exploding and vanishing problems. As is shown in Fig. 7, Du et al. [93] employed the long short-term memory (LSTM) [94], an important variant of RNN, incorporated with external factors to make a more accurate prediction. The design of the selective forgetting module makes it possible to learn long and short dependencies. However, the state a sensor monitors might not only be related to the historical data itself but also highly correlated with the sensors around it at the same time step. To extract the spatial and temporal

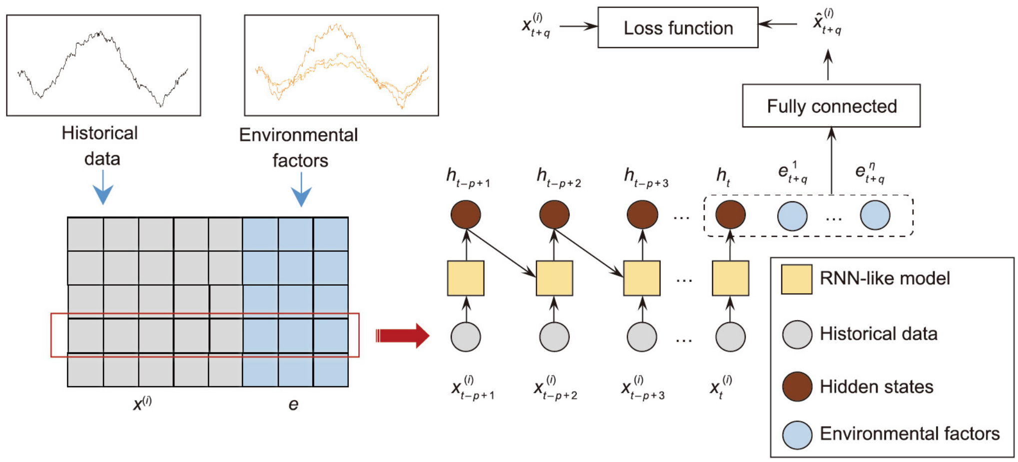

Fig. 7. Fusion prediction framework based on the RNN-like model. $x^{(i)}$ represents the raw data of ith sensor; e indicates the external factors; q is the number of forecasting time step, and η is the total number of external factors.

dependencies simultaneously, the graph convolution and time series forecasting could be integrated to form a unified framework, which has more potential to capture the dynamic of the states. However, this solution is still under the classical framework, so it is difficult to deal with the mutations in the value. Understanding the meaning behind the time series may be the future direction in this field.

8. Life prediction and preventive maintenance strategies

The service life of the structure can be evaluated from three aspects: ① The economical service life is the period during which structural maintenance is less economical than disassembly and replacement; ② functional service life is the period of time that the structure is used until it cannot meet the functional requirements; and ③ technical service life is the period of time when the structure is used until a certain technical index is unqualified, such as bearing capacity, integrity, or deformation. The residual life prediction here refers to the technical service life of the underground structure, that is, the time from the completion of the underground structure to the time when the structure cannot be effectively carried or experiences excessive deformation.

Before carrying out the life prediction, it is necessary to clarify what the predetermined functions of the structure include, and how to determine the failure of the structure function, that is, the durability limit standard. For the assessment and prediction of the durability of concrete structures, there are mainly the following criteria: ① Carbonization or chloride ion erosion takes time, and it occurs when the concrete protective layer is completely carbonized; it leads to the corrosion of the reinforcement. It is a critical point of the structural life, or in the chloride ion environment, the time when the concentration of the chloride ions on the steel bar surface reaches the minimum concentration that causes steel bar rust candles (which is taken as the life of the structure). ② The life criterion of cover cracking is the time required for the rust expansion crack along with the reinforcement on the concrete surface to become the critical point of the service life of the structure. ③ The crack width and steel corrosion limits occur when the width of the rust expansion crack or the corrosion amount of the reinforcement reaches a certain limit as the critical point of the service life. ④ The bearing capacity refers to the reduction of the bearing capacity to a certain limit as the durability limit standard.

The life prediction of underground structures can be divided into two categories: One is the study of material durability based on the environment of underground structures, and the other is the structural safety research based on material degradation, which does not consider the influence of underground structure stress on material degradation. A new research idea is to propose the force evolution model of an underground structure system in combination with the above two types of research, so as to reflect the interaction of various factors and the evolution of the internal force and safety of the tunnel structure.

To make the maintenance of underground structures have a high effect and cost ratio, active preventive maintenance should be adopted to prolong the service life, save costs, minimize the maintenance cost of underground structures in the whole life cycle, and obtain the best safe operation guarantee with the best maintenance cost. The core of the preventive maintenance concept is to prevent problems before they occur. Preventive maintenance is time-sensitive: if the best time is missed, its effect will be greatly reduced. Preventive maintenance plays an important role in reducing the whole life cycle cost of underground structures and improving the durability and service life of facilities, and also saves resources and protects the environment.

There have been many traffic safety accidents caused by inadequate maintenance and management, the damage of the durability of the structure without effective bearing, or excessive deformation, such as vehicle accidents caused by water seepage and freezing in tunnels, fans falling off, and fires in tunnels. There are hidden dangers to operational safety. We should carry out professional and systematic preventive maintenance of tunnels as soon as possible, and this maintenance should include the following: ① regular structural inspections, where we find abnormal situations, and determine the technical status of the structure, the functional status of the structure, and the corresponding maintenance countermeasures and measures; ② timely and preventive maintenance and repair of the structure, repair the slight damage of the structure, and keep the structure in a healthy condition; and ③ combine the IoT with the traditional operation mode to deal with the maintenance and management of underground structure groups on a large scale, forming the integration of inspection/monitoring. The digitization of maintenance, realization of intelligent evaluation, informatization of asset management, and scientific management decision-making can effectively improve the efficiency of maintenance work, delay the disease process, and prolong the service life of structures to obtain significant economic and social benefits.

9. Conclusions

The development of the underground space is the necessary step for future urban construction. Intelligentization plays a vital role in enhancing the competitiveness of China, and research attention should be focused on basic theory and the key technology. Combined with the IoT, novel infrastructure and computer science, an intelligent monitoring system could be established in a multi-source fusion manner. To construct a complete, effective, green, and reliable system, and promote the intelligent reform of urban infrastructure, three suggestions and future directions are proposed: ① Develop intelligent coordinated and holographic sensing equipment for infrastructure. With this equipment, the deep coupling and online spatio–temporal inference framework can obtain the entire structural state all the time. ② Promote the integration of underground and transportation infrastructure [95]. The full lifecycle of intelligent sensing, health diagnosis [96], and a security warning system should be built upon the combination of domain knowledge and data mining. ③ Orient toward sustainable infrastructure development. Being friendly to the economy, environment, and safety should be the goal of infrastructure development.

Acknowledgments

This work was supported by the National Key Research and Development Program of China (2018YFB2101003) and the National Natural Science Foundation of China (51991395, 51991391, 71901011, and U1811463).

Compliance with ethical guidelines

Bowen Du, Junchen Ye, Hehua Zhu, Leilei Sun, and Yanliang Du declare that they have no conflicts of interest or financial conflicts to disclose.

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