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Research on the Application of Machine Learning in Bridge Structural Health Monitoring

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Abstract. Bridge structural health monitoring (BSHM) is an effective measure to monitor bridge operation status, identify bridge damage and give early warning. In the era of rapid development of the Internet, the combination of computer algorithm and BSHM can greatly improve the efficiency and accuracy of monitoring. This paper discusses the application key of machine learning (ML) in BSHM. First, the basic concepts of BSHM and ML algorithms are outlined respectively. Then, the advantages of BSHM compared with traditional detection methods are analyzed. In addition, the composition, sensor technology, data transmission and data processing of the BSHM system are discussed in detail. Among them, data processing includes preprocessing, fusion, identification and visualization. In these processes, ML is particularly important, playing a crucial role in pre-processing and data analysis. Finally, the advantages and disadvantages of the application of ML algorithm in health detection are discussed, and its future development direction is prospected.

Keywords: Machine Learning; Structural Health Monitoring System; Data Processing; Bridge Engineering.

1. Introduction

As a significant transportation infrastructure, bridges need to bear the continuous impact and load of vehicles, people and natural environments such as wind and temperature changes. However, with the growth of service life, bridge structures may suffer from aging, fatigue and other problems, thus affecting its safety performance and causing great losses [1]. In order to confront these challenges, the bridge structural health monitoring (BSHM) system comes into being. BSHM is a system specifically designed to monitor and evaluate bridge structures and their environmental conditions, defined as an automated, continuous, real-time damage assessment process [2]. It can assist predicting possible structural problems and detecting potential damage ahead, thus better ensuring the safe operation and prolonging the service life of the bridge [1].

BSHM emphasizes the measurement of variations in physical parameters, and the sensitivity features extracted from consecutive measurements and the statistical analysis of these measurements can give the ability to assess the present behavior of the structure and thus the current state of the structure [3, 4]. The sensors are initially chosen and placed in strategic locations on the structure. The data gathered by the data acquisition system is transferred to the processing unit where it is stored and managed in a database system. A variety of techniques and algorithms are applied to ascertain the assessment of the collected data and the condition of the health of the system. Ultimately, based on the location and severity of damage identified and future proliferation, inspections and maintenance in the decision-making process are decided upon and implemented [4]. With the advancement and incorporation of algorithms, the BSHM is gradually improved and developed. For instance, in the monitoring data analysis method of the BSHM, the vibration-based damage detection technology in the model-driven method makes extensive utilization of artificial neural network, deep learning, machine learning (ML) algorithms, etc. [5, 6]. It's worth noting that the ML algorithm is playing an increasingly crucial role in BSHM.

This paper is aimed to discuss the application of ML in bridge monitoring. It begins with an overview of BSHM and ML algorithms, as well as a discussion of practical examples of ML algorithms in bridge health monitoring and the advantages compared with traditional monitoring methods.

2. BSHM

With the rapid advancement of large-scale bridge construction, BSHM has gained significant attention. Nowadays, many bridges incorporate real-time monitoring systems [7]. Bridge condition evaluation involves accessing inspection data through established technologies, analyzing the information, and assessing the safety, durability, and applicability of the bridge [8]. Regular evaluations help understand the bridge's structural status and guide maintenance decisions [9].

BSHM usually consists of three main parts, monitoring the structure with data collected by sensors, retrieving damage features, and analyzing the damage features to assess the status of the monitored structure [10]. Fig. 1 shows the steps of the BSHM system.

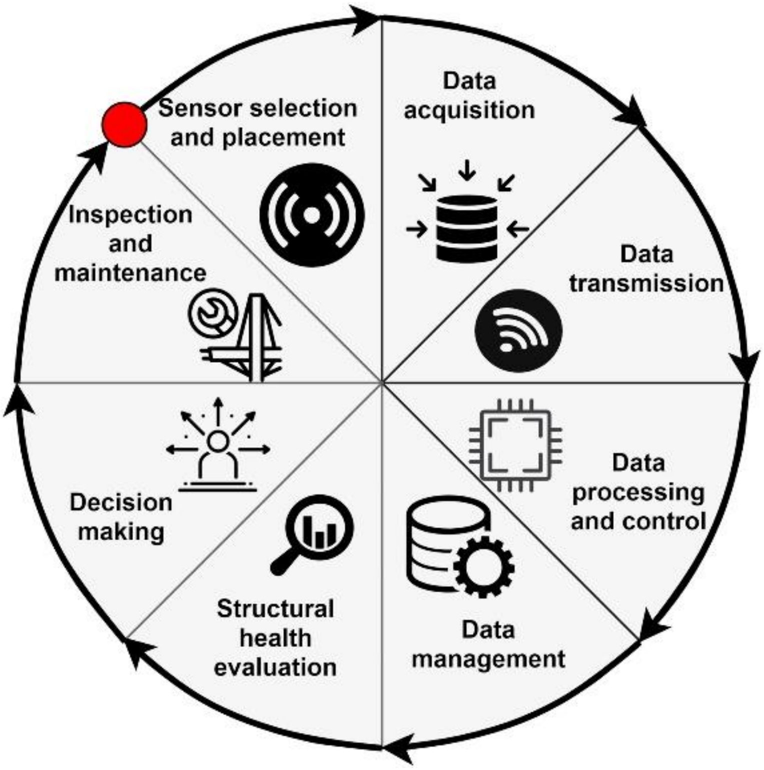

Figure 1. The steps of the BSHM system [4].

2.1. Sensor Technology

In BSHM, four main types of sensing technologies are widely utilized: fiber optic sensors, piezoelectric sensors, global navigation satellite systems, and magnetostrictive sensors [11]. The mentioned sensing technologies have their own advantages and disadvantages, then the application scenarios are quite different [9]. For instance, Fiber Optic Sensing (FOS) is ideal for long-term health assessment of bridges in most cases owing to its long-lasting, stable and insensitive to external disturbances. It is also lightweight and small enough to have little impact on the performance of the bridge [12]. As a result, it is frequently embedded in concrete for monitoring the health of bridges and is applied to infrastructure performance monitoring, including strain profile monitoring of large structures, as well as monitoring or tracking critical parameters such as temperature and pressure at various locations [12]. However, the similarity is that most of these intelligent sensors were designed to address the limitations of traditional sensors in terms of measurement precision.

2.2. Data Transmission

After collecting and storing the different types of monitoring data from the variety of sensors mounted on the monitored equipment, it needs to be transmitted to the base station. Most BSHMs employ wired transmission systems to produce monitoring information, which has the drawbacks of high cost, large scale, and inflexibility [13-15]. Hence, wireless sensing has become a hot research topic recently due to its advantages of low cost, low energy consumption, high fault tolerance. Specifically, wireless sensing technologies offer two main advantages. Firstly, they eliminate the need for connecting cables, significantly reducing the overall system cost. Secondly, the small size of wireless nodes allows for installation in locations where it is difficult to place cables. Additionally, wireless sensing can utilize various wireless transmission methods to accommodate different transmission distance requirements and facilitate multi-node transmission, ultimately enhancing wireless transmission efficiency [15, 16]. It is evident that wireless transmission has far better advantages than wired transmission and also is a technology worth continuing to explore [9].

2.3. Data Processing

Data processing is the process of analyzing and summarizing the massive sensing data in bridges using the suitable statistical analysis methods, to access the health condition of bridges. It is mainly composed of steps such as data preprocessing, data fusion, pattern recognition, data processing and data visualization [17]. Details can be found in the flowchart of data processing (Fig. 2).

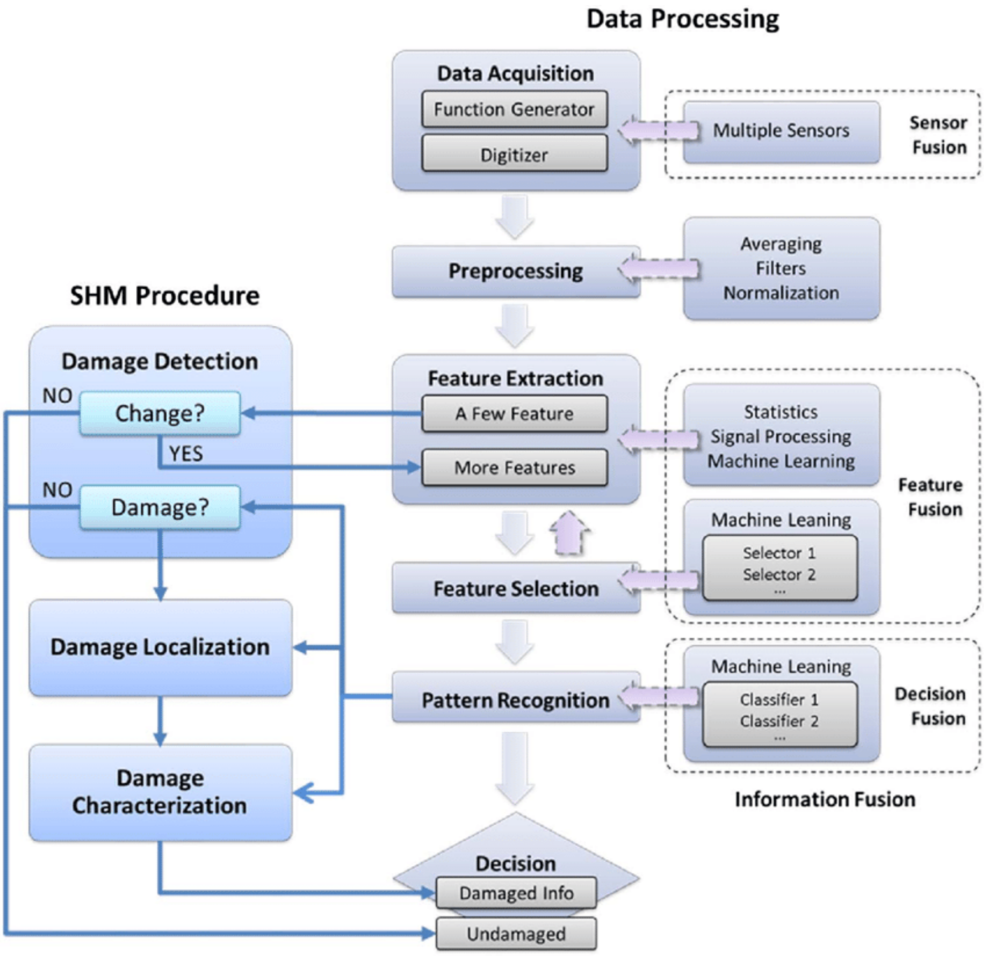

Figure 2. The flowchart of data processing [18]

The primary function of data preprocessing is to obtain the data sources relevant to the monitoring targets based on the specified requirements, verify the validity of the data within the mechanical constraints of the bridge, and generate the essential data that is ready for analysis in the subsequent step [19]. Among them, data classification is an essential step of data preprocessing, in which for easily recognizable and frequently occurring trends and outliers, supervised ML methods can be detected and supply the corresponding labels to construct a categorized dataset. Tang et al. [20] proposed an anomaly detection method based on the data preprocessing stage of convolutional neural networks (CNN), and it is evidenced that the Two-dimensional CNN model is the best for identifying the complicated time series data preprocessing in BSHM [2, 9].

Next, data fusion generally means the simultaneous use of multi-channel or multi-sensor datasets to gain more precise analytical results [21]. Some of the commonly used theories are Bayesian theory, single key evidence theory, Kalman filter theory, etc. [9].

Then there is pattern recognition. Pattern recognition algorithms comprise supervised learning and unsupervised learning. Supervised learning is classified into classification and regression, in which the classification method is mostly utilized for damage detection, load effect analysis, and the regression method is applied to describe the correlation between the dependent variable and the independent variable, which is primarily used for the analysis of load effect of bridges [22]. This step makes extensive use of ML algorithms.

Finally, the principal purpose of data visualization is to graphically display monitoring results in a clear and effective manner [23]. Parallel coordinate plot (PCP) is a well-known method for visualizing high-dimensional multivariate data, and through the function of pattern recognition, PCP can show the correlation between data [24, 25].

From the above, through the whole process of BSHM, the step that data processing is closely associated with computer algorithms. Among them, ML algorithms are even more important in the two parts of data preprocessing and data analysis, playing an extremely critical role.

3. ML

3.1. Classification and Basic Concepts of ML

ML is designed to teach machines how to process massive amounts of data more efficiently. Once the machine has collected the data, sometimes humans are unable to interpret the information extracted from the data [26]. In such cases, ML algorithms are utilized with the aim of processing, learning, and analyzing the data to better help humans make decisions.

ML relies on various algorithms to solve problems. Which algorithm is used depends on the specific situation, such as the type of problem one wishes to solve, the quantity of variables, the model that best fits into it, and so on [26].

Real-time and online damage evaluation features in BSHM systems are a transition to bridge the gap between the inefficiencies of past applications and the upcoming emerging technologies of the future. In the age of smart cities, Internet of Things (IoT) and big data analytics, the sophistication of data-driven civil infrastructure monitoring frameworks has not yet matured entirely. Thus, ML algorithms deliver the essential tools to empower BSHM systems and present intelligent approaches to the challenges of the past.

3.2. ML in BSHM

Generally, ML algorithms are predicated on either statistical methods, neural methods, or synthesized methods. The first two approaches are typically recognized as the primary pattern classifiers for BSHM. In order to test for damage using ML, a pattern class or category is firstly definedd [4]. Subsequently, the collected data may be assigned class labels or remain unlabeled, followed by preprocessing to eliminate noise or outliers and decrease the size of the damage vectors. Next is feature extraction, where damage-sensitive features are chosen based on engineering judgment, mathematical and transformation procedures, or a combination of both. Following it, post-processing can also be applied to further compress, regularize, or blend the data as necessary. After these phases, the damage state is identified using algorithms that one or more of the coming techniques, such as damage position, outlier detection. Next, each of these individual steps can be explored in detail as examples.

3.2.1. Data acquisition.

ML has a critical position in the optimization of sensors in the data acquisition system. The target is to employ the minimum quantity of sensors while ensuring maximum damage sensing performance. Various studies have proved that the most widely used ML algorithm in sensor optimization is the Genetic Algorithm (GA) combined with neural networks. In practice, ML models are commonly employed to reposition existing sensor locations to enhance overall system performance in terms of damage detection. It presents simple, adaptable and low-cost solutions compared to traditional methods [4].

3.2.2. Data cleaning.

There is an anticipation that the data collected from sensors will always be satisfactory and meet the required standards. However, external factors can compromise the quality of the data. In summary, data cleaning involves establishing strict criteria for discarding data and excluding it for re-entry [27]. Prior to the implementation of any BSHM, five different quality criteria metrics must be considered, availability, usability, reliability, relevance, and presentation quality [23]. Data harmonization is crucial for ensuring the efficiency and accuracy of ML. In the context of BSHM, typical data cleaning is achieved through software or hardware filtering approaches integrated into data acquisition devices. Techniques such as noise suppression using low/high band-pass filters, resampling, or other methods can be employed. Additionally, for handling large datasets with compression requirements, ML algorithms are utilized to perform data reconstruction, transforming irregular data into its corresponding complete form [4]. Data cleansing process is always conducted prior to initiating the follow-on ML process.

3.2.3. Data compression.

BSHM-equipped structures are composed of tens or hundreds of diverse sensors. Over a long duration of monitoring, a large amount of data will be generated and not every feature produced can be used for analysis. Data compression, in simple terms, is the downscaling of features, allowing for only the most statistically meaningful and damage-sensitive features to be extracted [4]. One solution to this problem is to fuse the sensor arrays to extract similar features, e.g., gathering different modal vibrational patterns at each sensor node and then compressing them to generate a low-dimensional feature vector containing only the first few modal vibrational patterns [4]. The most traditional method involves using linear principal component analysis (PCA) in conjunction with ML. This is because ML have a limitation: when learning from high-dimensional data vectors with a finite number of exogenous variables, data compression often results in a loss of the ability to learn patterns [28]. Then if sufficient features are not extracted after compression, it is impossible to infer whether the algorithm can be treated as a damage identifier. So before training a ML model, the data may need to go through a PCA process to reduce the number of features, remove noise, or eliminate multicollinearity. This can make subsequent ML algorithms perform better.

3.2.4. Feature extraction.

Feature extraction is a process that transforms the gathered data into a more accessible form that is easier to recognize and can be quickly captured by any simple ML algorithm [4]. The most vital aspect of this step in any ml-based BSHM is to find a method for extracting and selecting the sensitivity features extracted and properly associated with the damage [4]. The majority of these are performed using data-driven, model-driven techniques, wave propagation and impedance-based methods. For instance, the sensitivity features extracted in the data-driven method can be realized by using time-domain, ML algorithms and so on. Time and frequency-domain waveform analyses cannot accurately show the site of damage and necessitate a large amount of data for sensitivity analyses, with inconsistent reproducibility of the model over diverse time frames. These drawbacks can be overcome by combining ML algorithms with their inherent features in terms of extracted data or character selection [29].

3.3. Summary

In the framework of BSHM, the most popular learning algorithms are supervised, unsupervised and semi-supervised. In rare cases, when the engineering structure has both worn and intact data, supervised learning is the preferred learning method [4]. In these situations, unsupervised learning is used to owing to the lack of damage data, which is the preferred approaches for most civil infrastructures [30]. The most common example of this is the support vector machine (SVM). It can map linear and nonlinear data to an n-dimensional feature vector where hyperplanes group features into classes while maximizing the margins between them. SVMs are often superior to supervised ML algorithms because of their ability to perform high-quality predictions [31]. In addition, ML algorithms such as neural networks, Gaussian mixing, and correlation analysis are also used extensively in BSHM systems. Different algorithms have different advantages and disadvantages and have their own applicable steps.

More notably, the combination of ML and IoT is also promising. For example: The IoT revolves around interconnections, which may lead to situations where multiple sensors are utilized to collect diverse data of varying sizes and resolutions. Processing and correlating such massive amounts of data can be computationally intensive. In this context, ML can be employed to make inferences and establish relationships between multiple signal sources, enabling the recognition of damage [4].

4. Conclusion

It can be seen that ML algorithms rely on massive, high-quality data for training and prediction. In BSHM, sensors and monitoring devices are installed in various parts of the bridge to collect multi-dimensional data such as vibration, temperature, humidity. These data provide a rich source of information for the ML algorithms, which allows the algorithms to more accurately assess the health of the bridge. Then in the data processing process, a multitude of ML algorithms are applied, including SVMs, random forests, neural networks, and so on. Each of these algorithms has its own strength and weakness and is suitable for different monitoring scenarios and needs.

In the future, ML algorithms will be deeply integrated with other advanced technologies such as IoT and big data to form a more intelligent and efficient BSHM system. This will further improve the real-time and accuracy of monitoring and provide a stronger guarantee for the safe operation of bridges. With the continuous deepening of algorithm research, the application of ML algorithms in BSHM will be optimized continuously. In summary, the application of ML algorithms in BSHM has a broad prospect. With the continuous progress of technology and in-depth promotion of application, ML algorithms will provide a more comprehensive, accurate and efficient guarantee for the safe operation of bridges.

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