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Integration of Topological Data Analysis (TDA) in Structural Health Monitoring (SHM) for Civil Engineering

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ABSTRACT

Structural Health Monitoring (SHM) is critical for ensuring the longevity and safety of civil engineering structures. Traditional SHM techniques often struggle with the high-dimensional, complex data generated by modern sensor technologies. Topological Data Analysis (TDA) offers a robust alternative by capturing the underlying topological features of this data, enabling more accurate and efficient monitoring. This paper explores the integration of TDA into SHM, discussing its theoretical foundations, practical benefits, and challenges. We review recent advancements, including deep learning enhancements and real-world applications, highlighting how TDA can improve damage detection and predictive maintenance. Future research directions are proposed to further the adoption of TDA in SHM, emphasizing the need for real-time, industrial-grade solutions.

Keywords: Structural Health Monitoring, Topological Data Analysis, Civil Engineering, Persistent Homology, Damage Detection, Deep Learning

INTRODUCTION

Structural Health Monitoring (SHM) is a critical field within civil engineering, focused on ensuring the safety, longevity, and reliability of structures such as bridges, buildings, and other infrastructures [1-3]. SHM involves the continuous assessment of structural integrity through the collection and analysis of data from various sensors embedded within the structures. This process is essential for detecting damage early, preventing catastrophic failures, and optimizing maintenance strategies [4, 5]. In recent years, the field of SHM has seen a surge in interest due to the advancements in sensor technology and data analysis methods. However, traditional SHM techniques often face challenges in handling the vast amounts of high-dimensional data generated by these sensors. Conventional methods, which rely heavily on signal processing and statistical analysis, can struggle to identify subtle patterns and anomalies that are indicative of structural issues. This is where Topological Data Analysis (TDA) comes into play [6, 7].

TDA is a relatively new mathematical framework that focuses on the shape of data. Unlike traditional methods that often rely on linear assumptions and Euclidean metrics, TDA captures the topological features of data, such as connected components, holes, and voids, which are invariant under continuous deformations. These features are crucial for understanding the underlying structure of the data and can provide more robust and insightful analyses [8, 9]. The intersection of TDA and SHM represents a promising frontier for civil engineering. By leveraging TDA, engineers can extract meaningful patterns from complex, high-dimensional data, leading to more accurate and efficient SHM systems. Recent pioneering research has demonstrated the potential of TDA in SHM [10, 11, 12] such as the work by [13], which used TDA to classify features from structural time series data recorded under different configurations. This paper aims to explore the integration of TDA into SHM. We will discuss the fundamental concepts of TDA, its advantages over traditional methods, and its application in SHM. We will also review recent advancements in the field, including the use of deep learning techniques, and present case studies that highlight the practical benefits of TDA in real-world SHM scenarios. Finally, it will also study future research directions further to enhance the adoption and effectiveness of TDA in SHM, ensuring that our infrastructure remains safe and resilient.

Structural Health Monitoring (SHM)

In recent years, relevant pioneering research has been carried out at the crossroads of Topological Data Analysis (TDA) and SHM, given the exploration of TDA to describe and recognize structures in high-dimensional sensor data characterizing structures [14, 15, 16]. This includes a study where the features retrieved from a Structural Time Series (STS) recorded in different configurations were classified using TDA [13]. TDA is concerned with donor-independent, robust, and combinatorial descriptors, allowing empirical datasets to be sought, as is received. What even is different in topology from more traditional descriptors, which the crowds in the field of engineering might be more familiar with, as they are effectively designed for manifold learning, than ones like principal components or signal processing filters [17, 18, 19]. To ensure the longevity of infrastructure and the safety of people and properties, it is important to assess the structural health of construction works on a regular basis [20-23]. Structural Health Monitoring (SHM) is the process of implementing a damage detection strategy for construction works and encompasses data collection, data analysis, and decision-making [24-27]. SHM can help to address requirements for damage surveys and safety assessments, reducing dependency on visual inspections and simplifying the maintenance plans of in-service constructions and validation plans on new realizations [29-31]. Current SHM is mainly designed for specific applications and is challenged by a high volume of data being offered and the tendency to generate a high volume of data, especially if continuous monitoring is required. For instance, in the case of strain-based SHM events, the sensor data is collected at high frequencies, regularly [32-35].

Importance of SHM in Civil Engineering

In recent years, new learning-based methods, combining machine learning and deep learning techniques, are under development and are useful for SHM applications. This approach can be beneficial for SHM applications because feature extraction, which was manually designed in many conventional methods, is automatically done when using a deep learning technique. Even better, it is possible to use labeled data to train the method to adapt to changes in measurement conditions which are common in SHM applications [36-38]. For example, Convolutional Neural Networks (CNNs) can automatically extract features and output the classification results [39-43]. There are several types and wide ranges of deep learning techniques available that can be applied to the SHM and modal analysis, for example, deep autoencoders, recurrent neural networks (RNN), and Long-Short Term Memory (LSTM) networks [44-47]. It is of great importance to ensure that the civil engineering infrastructure remains safe for public use. Structural Health Monitoring (SHM) can be used to prevent malfunction and collapse [49-50]. Infrastructure malfunction may surface in unexpected manners, makes it difficult to evaluate the structural condition based on the design documents and construction records only. Many SHM-related techniques have been developed over the last several decades [51, 52]. Modal analysis is one of the most popular techniques for SHM applications because it can enable early damage detection an enable predictive maintenance [53]. However, it has been pointed out that the signal processing of the time-series data is computationally expensive for real-time applications [54-56].

Fundamentals of Topological Data Analysis (TDA)

In this survey, the core components and basics of TDA are introduced, focusing on the problems of persistence and topological feature extraction [57, 58]. Various concepts in TDA are explained with the aim of providing an introductory guide on how to apply TDA to signal and image processing applications [59, 60]. As a part of persistence, homology groups are the most significant. Persistent homology measures homology groups at different filtration scales for a given metric space. The work of Edelsbrunner et al. uses an algebraic tool to measure the multi-scale cavities; hence, holes that persist across consecutive scales are considered important in TDA analysis [61]. Structural Health Monitoring (SHM) refers to the process of implementing and applying modern data mining techniques to structural monitoring systems to obtain structural and behavioral information and parameters [62-64]. Owing to the large volumes and high dimensions of the data in SHM, it is essential to ultimately interpret the high-dimensional data in a format that can be readily processed to make effective decisions regarding structural maintenance and timely replacement [65, 66]. Traditional signal processing and time series analysis methods fail to discover important features as they assume a Euclidean metric among times series or measurements [67]. However, in real-life scenarios, the underlying structure of the data might not satisfy these assumptions. Topological Data Analysis (TDA) captures these topological properties and has shown promise in extracting crucial features relevant to SHM applications [68].

Basic Concepts and Principles

To perform TDA, we first have to construct a simplicial complex, a topological space derived from a dataset. The simplicial complex regularly comprises vertices, edges, triangles, and higher-order simplices that bridge together collections of vertices. Often the construction of the simplicial complex is through a selection of sensing or data reduction method, data de-noising algorithm, distance metric, and thresholding: by being part of the TDA pipeline, the simplicial complex relates directly the structural choice made with the persistence barcode and derived indicators [69, 70]. After building a simplicial complex, TDA characterizes its structure (i.e., geometry and/or topology) through homology; a concept drawn from algebraic topology permitting quantifying cycles and cavities or holes. Homology computes from the simplicial complex a set of integer vector spaces or homological groups. Each of those groups topological features of a given dimension from the simplicial complex, and its cardinal ordinals represent the number of features in this dimension [71, 72]. Topological data analysis (TDA) is a mathematical discipline that creates and implements frameworks for extracting information from multidimensional data by examining the shape of its structure [73, 74]. Originally developed in algebraic topology, TDA has since found applications across several scientific and industrial fields. Although some of TDA's successful applications are despite its theoretical complexity, it can be methodically studied and experimented with to extend to particular needs, and as such, constitutes an emerging field of interest in structural health monitoring (SHM) [15]. As TDA generalizes well into higher dimensions and allows a broader viewpoint into the engineered systems, SHM community may acquire from it a new control to understand and mitigate structural malperformance. One of the immediate advantages that TDA techniques provide to SHM practitioners is their ability to interrogate and visualize multi-dim spatial or temporal data in low dim without discarding relevant geometrical information.

Integration of TDA in SHM

With the rapid progress of complexity, there is a need for effective SHM strategies to ensure system stability and structural safety with minimal damage risk. Fortunately, TDA provides an opportunity to define many parameters and indices mathematically for quantitative vibration analysis. It can also filter out signals of low amplitude or high noise by arraying or adopting TDA while analyzing vibrating systems. With the help of in-phase and quadrature (I/Q) plots, TDA is extremely beneficial for early detection. The cases in order to find the areas where scatter points are placed and also to understand if the effect of damage is negative or positive on repair process is another aspect. Also, along with the TDA index, the entire mentioned real-valued TDA approach is non-straightforward and plays an important role in the universality area. This has emerged as a general field that has become an interdisciplinary work area and today covers many academic and industrial fields over the years [75, 76]. TDA as an alternative method to classical tools to the detection or recognition damage or repair is very fast, low-cost, accurate and less time consuming, as well as or more reliable than classical vibration-based SHM techniques would have a wide range of applications. The fatigue of structures under dynamic loading is difficult to monitor with traditional methods. Non-Destructive Testing and Evaluation (NDT/NDE) aim to inspect materials and/or structures for their present condition without altering their serviceability [77, 78]. On the other hand, Structural Health Monitoring (SHM) characterizes and evaluates the condition of materials and/or structures for the performance of an in-service structure [79, 80]. In practice, TDA is a suitable candidate, as the concept of in-phase and quadrature polarization can be generalized to an arbitrary real numerical structure. Such developments not only demonstrate the immense impact of TDA, regarding many mathematical vibrating systems, but also the various techniques to study and observe the behaviour of the systems of this type [13]. These discussions led to several possibilities of different real-valued TDA structures where we can provide some basic properties of the systems and study the vibrational responses of different structures/lines by using vibration analysis in the field of SHM. The values of topological indices give us crucial information about topological structures under different damage situations. This is an incredibly compact and simple approach that can be used with high precision in, a range of research fields ranging from medicine to SHM [81-84].

Benefits and Challenges

The biggest challenge with the traditional pairwise comparisons-based distance matrix construction is that the computational cost scales quadratically with the data size due to the similarity neighborhood radius environment [85-87]. To overcome this challenge the use of information snap-sampling with information snap-sampling wavelet transformation and dimensionality reduction techniques will be employed in the research. Also, those domains which are mainly filled with linear and continuous data than feature space will be neglected which enable a much rapid computational scheme. Recognition exception of TDA map to input feature space is another challenge as TDA topological stratification maps might not come up with correct with the original feature space. Though TDA a topological data analysis algorithm does not give any topological or geometrical data information but has the potential to be a high-valued and much efficient classification model. TDA and its various algorithms did not support well-corrupted or noisy data [88-90]. Topological Data Analysis (TDA) has been increasing which is largely used as a data preprocessing tool for Conducting Structural Health Monitoring (SHM) [15]. Its topological features can tolerate noise in the system and provide an automated solution eliminating the need for thresholding and intricate labelling procedures. The traditional image and data processing methods usually extract topological information from a distance matrix in which the input data points first convert into a pairwise geometric distance matrix [91]. The two biggest benefits of the TDA data processing procedure are that (i) no similitude function or neighborhood radius is required, and (ii) parameter prominence is low. The enriched information filled in the obtained graphical-geometric tree-like structure provides several scales of a system. Barcodes, turned out to be an accurate and concise topological descriptor of a data metric space, where various statistical classifiers can be employed for structural damage classifications [92].

Case Studies and Applications

Vision-based techniques have gained the attention of researchers lately, as these are highly adaptable and do not require surface-attached sensors. The vision-based techniques in practice have the potential to create an automated, economical, and reliable platform which helps mitigating infrastructure evaluation and inspection concerns. A few decades ago, due to manual inspection incompetency, civil infrastructure evaluation had become a concern of researchers and practitioners. There were numerous challenges in the implementation of automated image-based techniques. To overcome these challenges, 3D reconstruction techniques were developed. These 3D reconstruction techniques help mitigate inclined camera orientation and the close vicinity of the camera to the target structure. Therefore, in this attempt, authors re-cognize 2D vision-based techniques as they are more attractive regarding stroke structure evaluation. Image processing algorithms and the latest advancements in computer hardware have revolutionized vision-based techniques in recent years, and the authors believe that this technique will have a significant impact in the domain. These automated platforms possess the potential of frequent and simple visual infrastructure inspection, ensuring the shrewdness of the proposed strategy [93, 94]. Area-wise distributed monitoring using long gauge sensing techniques is one of the least applied applications in Engineering. The system offers the ability to diagnose single-sensor failure and significantly reduces the data requirement to model high-dimensional datasets. Dimensionality reduction follows the feature extraction and typically involves principal component analysis, multidimensional scaling, ISOMAP and various kernel methods. The key insight for using TDA as a paradigm for dimensionality reduction is that the topological signature can be preserved in embedded spaces of much lower dimensions. Optimal TDA representations are typically obtained by extending standard linear projection methods with one form of topological contraction. One relatively recent advancement in TDA for SHM is community detection which aims at detecting or possibly clustering the prominent features in topological space [95, 96]. In practical TDA-based SHM implementations, the birth and the death cycles of clusters must be preserved in the embedded space, which is realized in the form of discrete Morse functions. A wide array of TDA-derived 'topological signatures' for SHM is provided through the homological analysis. The fundamental property of all homological characteristics is their stability when embedded in different dimensions, i.e., they are robust against noise. The application of TDA in SHM mainly consists of two major categories, which are feature extraction and dimensionality reduction. With the introduction of concepts from topology, TDA projects high-dimensional data into low-dimensions. The central motif behind TDA is to preserve cluster statistics by contracting bunches of points in the embedded space, while 'stretching' them as a few connected components and bubbles, possibly. As such, designs of TDA for SHM should sufficiently 'amplify' the topological signature of responses while 'attenuate' the topological signature of noise [15, 97, 98].

Real-world Examples of TDA in SHM

Through the study of different real-world cases, we have learned that TDA approach can be successful in detecting damage's presence and location and to some extent, assessment of the severity if used properly. The method has shown potential to work on a different kind of datasets of Civil engineering structures. We also learnt that some theoretical knowledge of the system could be essential for the successful application of TDA in SHM tasks [99]. [15], are the first to apply TDA in SHM and provide a good example of the successful application of TDA in SHM but on a large-scale test, synthetic data. Magliacano et al. and Behzadan are among the first ones to apply TDA in SHM and use the theoretical knowledge of physical systems to limit spurious topological features and distinguish them from damage signals. Khosravifard et al. are the first to deal with 3D data in SHM. Despite this, they avoid using the TDA, reduce the dataset to 2D, and the method to PCA, instead. Lonkar et al. and Saadat et al. are among the first to introduce TDA applications in SHM, but they do not provide real-world applications yet. Vinciarelli et al. were among the first to apply TDA in SHM but suggest nonlinear differential equations for estimating the noise level of original data which is not physically grounded. Foerster et al. proposed Physical before selecting TDA parameters suggesting filters on original data for removing noise. Mussone et al. are among the first ones who preprocessed original data by applying some filtering. However, they did it merely to reduce the amount of data [15].

Future Directions and Potential Research Areas

Consequently, future work should primarily aim to fill the gap of providing industrial-grade, fast, and efficient TDA-driven SHM tools that could be embedded in real-time SHM systems deployed on complex engineering systems. Furthermore, the extension of the study of topological persistence for the Warhammer, Lebesgue and Betti numbers categories can be seen as fruitful research opportunities in structural label prediction tasks. The efficiency of the Warhammer and its derived persistence metric in capturing subtle intraindividual behaviors and its potential adaptation in SHM studies is worth exploring in the literature [100]. On another front, this field can benefit from research-driven studies on finding benchmarks on performance metrics such as fixed or variable thresholds, area under the receiver operating characteristics, linearity, and out-of-sample validation results of various statistical models [101]. In recent years, the field of TDA has seen an influx of attention, particularly in computational sciences and engineering communities. This popularity surge is underpinned by the fact that TDA represents a continuous and flexible framework to handle complex and highly non-linear data such as sensor readings from dynamic systems [102]. However, this methodological strength has not translated into civil engineering domain uptake. Even though recent research studies put forth proof-of-concept models in the applications of TDA for various diagnostic purposes that are relevant to SHM, these works inclined towards a descriptive manner and lacked real-time SHM applicability. The synergy of TDA methodology with high-fidelity structural time-series sensor data is a largely underexplored subject in civil engineering. By leveraging the non-linear dynamics of such signals, the TDA could provide a contribution that other data-intensive methodologies are limited to deliver [103].

CONCLUSION

The integration of Topological Data Analysis (TDA) into Structural Health Monitoring (SHM) presents a significant advancement in the field of civil engineering. TDA's ability to process and interpret high-dimensional, complex sensor data offers a robust alternative to traditional SHM techniques. By leveraging the topological features of the data, TDA enhances damage detection and predictive maintenance, providing a more reliable and efficient monitoring system. Despite the challenges, such as computational complexity and the need for real-time applicability, the benefits of TDA are substantial. Future research should focus on developing industrial-grade TDA-driven SHM tools, improving real-time analysis capabilities, and exploring new topological metrics. The synergy between TDA and SHM holds great potential for advancing the safety and durability of civil engineering structures.

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