Improvising Communication System by High Density Fibre Optic Cable using IoT Notifications

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Abstract:
We present a nondedicated bridge health monitoring (BHM) system that uses distributed acoustic sensors embedded in existing telecommunication fiber-optic cables to gather bridge dynamic strain responses. Our telecommunication cable-based system enables effective and affordable BHM without the need for on-site sensor installation and maintenance. However, due to the high measurement noise and error propagation in this nondedicated strain data, it is difficult to extract bridge damage-sensitive information (such as natural frequencies and mode shapes). We create a physics-guided system identification technique that simulates strain mode to get around the problem. Forms based on bridge dynamics-derived parametric mode shape functions that are governed by physics. We next analytically double-integrate the modelled strain mode shape to determine the displacement mode shape function. By limiting strain and displacement mode forms with respect to bridge dynamics, our technique increases the precision of calculating bridge damage-sensitive features and decreases error propagation. On a continuous three-span concrete bridge in San Jose, California, we tested our technique. With a precision of one metre, our algorithm was able to rebuild the strain and displacement mode forms and effectively identify the first three natural frequencies.
Keywords: Improvising, Communication, System, high, Density, Fibre, Optic, Cable, IoT, notifications.
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1. Introduction

Bridges connect people, roads, railroads, and other types of transportation infrastructure. However, in 2019 [1], almost 140,000, or 22% of the more than 617,000 bridges in the United States, were deemed to be physically or operationally outdated and needed immediate maintenance. Therefore, maintaining the safety and dependability of our bridges requires a comprehensive and efficient bridge health monitoring (BHM) strategy.

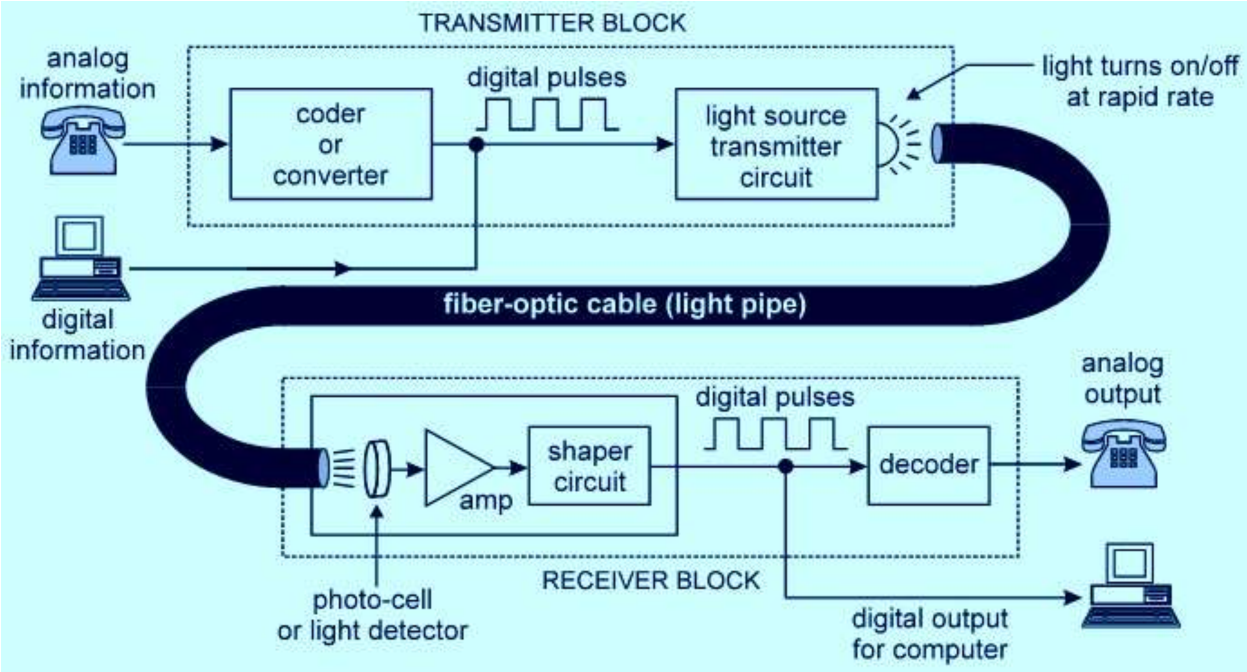

Fig.1: Improvising Communication System by high Density Fibre Optic Cable using IoT notifications.

Currently, bridge conditions are tracked via manual inspection [2] and specialised sensor instrumentation [3]. The majority of bridges' principal BHM technique involves manual inspection by qualified inspectors, although this method is time-consuming, labor-intensive, and potentially dangerous [4]. Dedicated sensor-based BHM approaches that install sensing devices directly on bridges were introduced to address these drawbacks. However, these approaches are also expensive and ineffective because they call for on-site installation and maintenance of the dedicated sensing equipment and instruments on each bridge of interest [5].

Numerous academics have recently suggested mobile sensing techniques for BHM to increase scalability and effectiveness. For instance, obtaining visual and dynamic data by scanning the bridge with unrestricted vehicles (such automobiles and unmanned aerial aircraft) [6–10]. Due to their mobile sensing nature, these mobile sensing methods are only able to record a limited amount of temporal information at each coordinate of the bridges, which limits their capacity to continually infer and diagnose bridge issues.

2. Pre-Existing Telecommunication Fiber Cables

We start by outlining the fundamentals of DAS in order to provide readers a baseline understanding of our BHM system, which employs distributed acoustic sensing (DAS) via already-existing telecommunication lines. A long-distance fiber-optic cable is used by DAS, a developing technology, as distributed virtual sensors to record ground vibration along the cable at high spatial and temporal sampling rates. A DAS system has an interrogator device and a common optical fibre. The interrogator unit injects brief laser pulses into the optical fibre and detects Rayleigh backscattering caused by the optical fiber's inherent inhomogeneities.

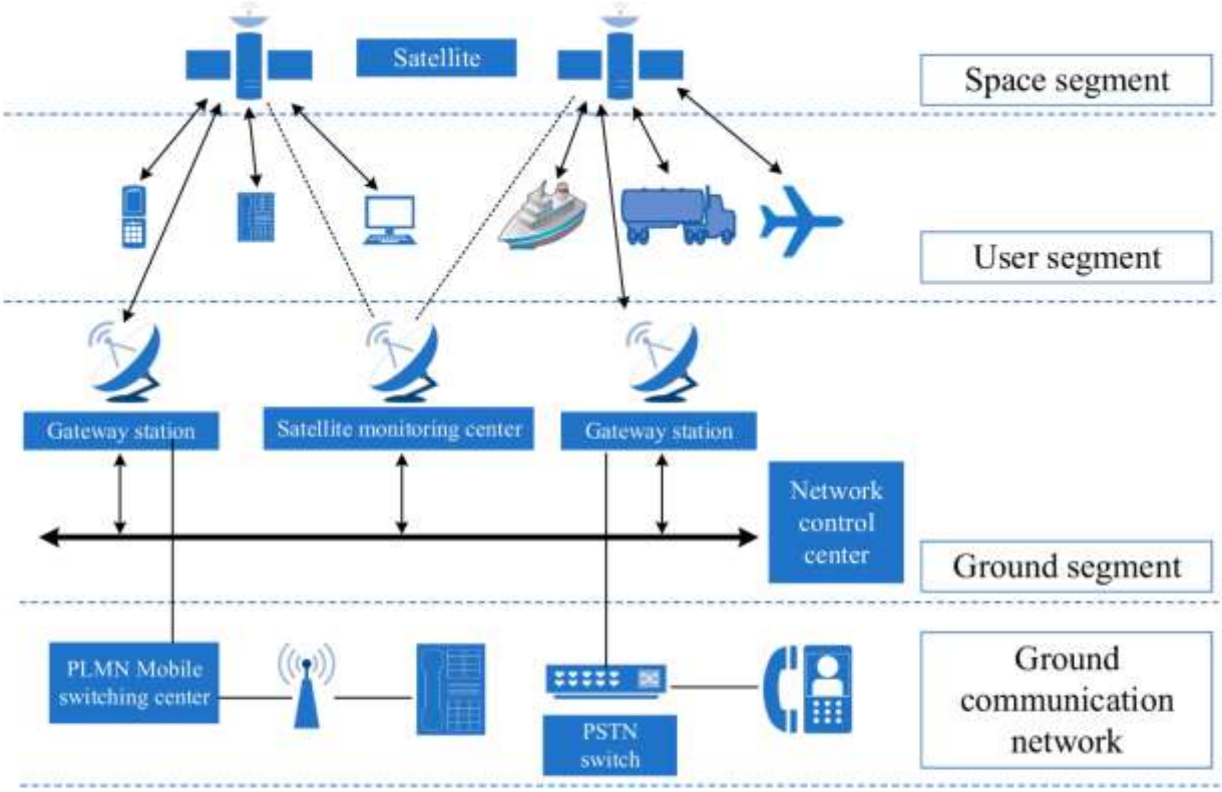

Fig.2: Improvising Communication System by high Density Fibre Optic Cable using IoT notifications process.

[5]. The strain or strain rate measurements exerted on the fiber-optic cable may be linearly translated to the optical phase change between the outgoing and backscattered laser pulses using optical reflectometry [19]. DAS has gained more attention in recent years due to its benefits over conventional single-point sensors in geotechnical applications [2, 4, 9] and urban monitoring [13]. In contrast to point sensors like geophones, fibre Bragg gratings (FBGs), and accelerometers, modern DAS can achieve meter-scale spatial resolution on a fiber-optic cable of tens of kilometers in length, resulting in tens of thousands of sensing channels [2-8]. This is because point sensors have low spatial resolution due to their high cost per unit.

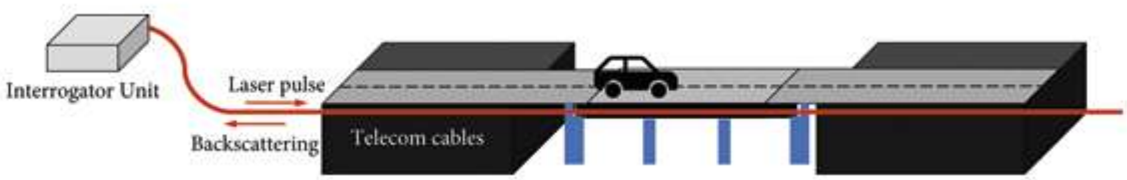

Fig.3: Improvising Communication System by high Density Fibre Optic Cable using IoT notifications Process.

Elemental Strain State-Space Model Identification

The two phases in the module for identifying the fundamental strain state-space model are (1) modelling the strain response to traffic load as stochastic dynamic processes, and (2) estimating the system parameters using the SSI-data technique. After that, damage-sensitive characteristics for bridges are calculated using the estimated system parameters. In the paragraphs that follow, we outline the two processes in depth. First, bridge dynamics including DAS reactions from communication cables are theoretically formulated using an elemental strain state-space model. The state-space model, the differential equation model, the impulse response model, and the transfer function model are the four traditional representations of a dynamical system [28]. We employ the state-space model because it (1) uses the state and output equations to model the physics and measurement systems, respectively, and (2) is a more compact and practical representation for multiple-input-multiple-output (MIMO) systems when compared to other dynamical system representations.

Physics-Guided Displacement Mode Shape Estimation

The physics-guided displacement mode shape estimation module contains two steps: (1) constraining strain mode shapes with parametric functions based on bridge dynamics and (2) estimating displacement mode shapes through analytical double integration. The details of the two steps and explanations are provided in the following paragraphs. To ascertain the connection between the displacement mode shape and the strain mode shape, we first review the bridge dynamics. Specifically, a shear force's minimal impact on the deflection is assumed to be caused by an Euler-Bernoulli beam with a span more than 10 times the height of its cross-section. In order for the longitudinal strain to be proportional to the beam curvature, we additionally assume that all of the strain measurement spots are spaced equally from the neutral axis of the beam.

As a result, the strain mode forms calculated in the first module of our technique must be twice integrated in order to estimate the displacement mode shapes. Both numerical and analytical methods can be used to conduct this double integration. Conventional numerical and analytical double integration methods, such as the trapezoidal rule [39] and analytical integration with a polynomial basis [6], would, however, produce inaccurate results because of the large measurement noise and uncertainty of DAS responses from telecommunication cables as the error propagates in the integration steps.

To this end, we estimate the displacement mode shape by first fitting a physics-guided shape function to the strain mode shape and then double integrating the fitted strain mode shape. In this way, we do not have the instability problem caused by numerical double integration and improve the estimation accuracy of analytical double integration by physically constraining the strain mode shape.

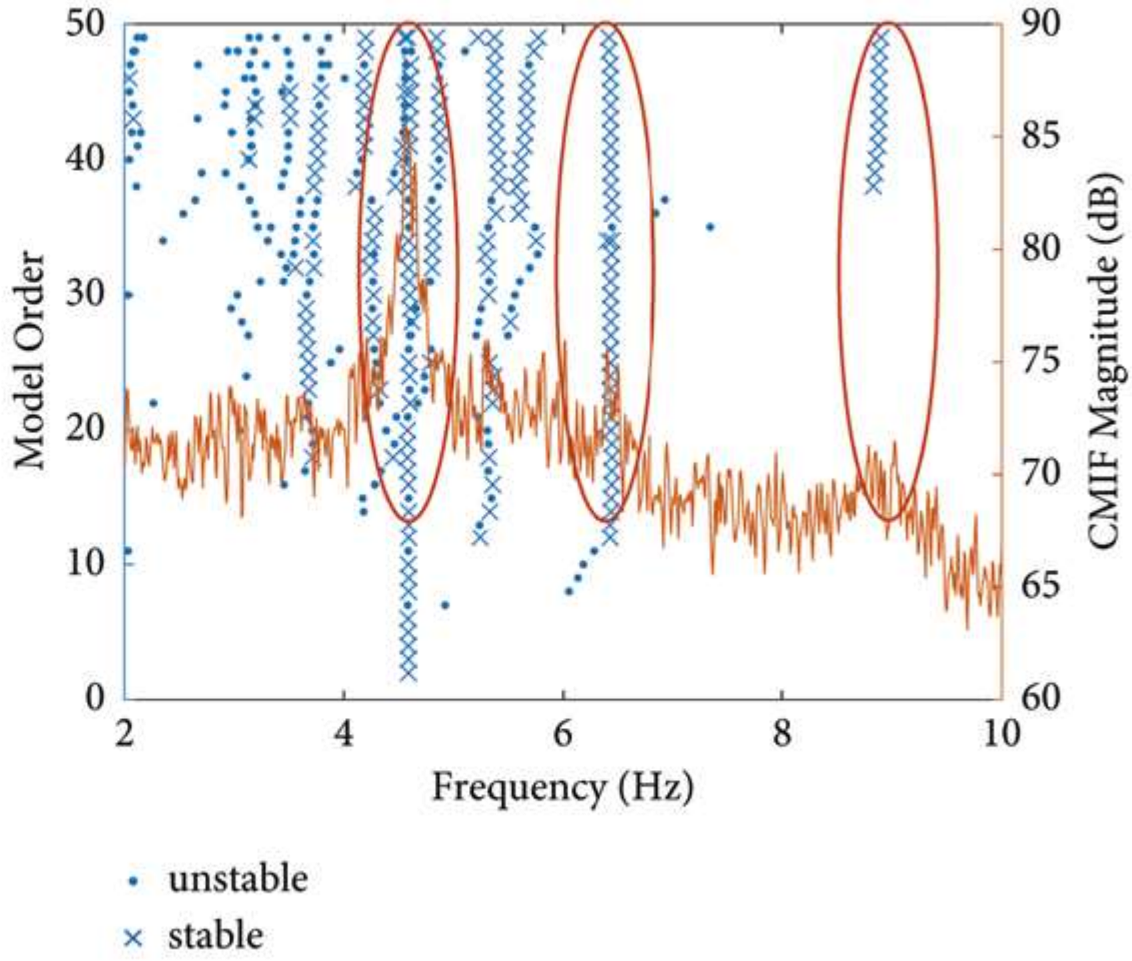

Fig.4: Improvising Communication System by high Density Fibre Optic Cable using IoT notifications Graph.

3. Results and Discussions

This section presents evaluation results and discussions of our system performance for telecommunication cable-based BHM, including bridge natural frequencies identification and strain and displacement mode shapes estimation. Using the stabilization diagram, we first assess how well our algorithm identified natural frequencies. In modal analysis, a stabilization diagram is a common tool for displaying and identifying a structure's modes [30]. In a model order vs Eigen frequency diagram, it depicts the detected modes. The SSI-data approach is used to estimate the Eigen frequencies and Eigen values at each model order.

Form modes. When the stabilization criteria in the predicted modal parameters between two successive model orders are lower than particular threshold values, the mode of a structure is stable; otherwise, it is an unstable mode. The stabilization criterion is specified for the Eigen frequencies as a mean percentage absolute difference, and for the mode shapes as one minus the value of the modal assurance criterion. In our work, the stability criterion values are the same as those used by Van Overshoe et al.

4. Conclusion

Using pre-existing telecommunication cables as distributed acoustic sensors, we present a nondedicated BHM system in this study to record bridge dynamic strain responses. Bridge damage-sensitive dynamic parameters, including as natural frequencies and strain and displacement mode shapes, are effectively estimated by the method. By utilising widely spread telecommunication fibre cables, it makes it possible for a cost-effective and efficient BHM since it eliminates the need for on-site sensor and equipment installation and maintenance. To be more specific, we created an elemental strain state-space formulation and then. To get around the issue of unreliable estimates for the dynamic characteristics brought on by the significant measurement noise of DAS reactions from telecommunication cables, we propose a physics-guided analytical double integration approach. The system was assessed using a concrete three-span bridge and validated using a traditional accelerometer-based method. With a mean absolute difference of 0.055 Hz between the first three bridge natural frequencies found by our technique and those determined using a typically used accelerometer system. A 0.800 modal assurance criteria is also used to estimate the strain and displacement mode shapes, yielding improvements of 72% and 11% over the two baseline approaches, which employ standard numerical and analytical double integration, respectively.

References

1. R. A. Hartle, T. W. Ryan, and E. Mann, *Bridge Inspector's Reference Manual: Volume 1 and Volume 2*, Federal Highway Administration, Washington, DC, USA, 2022.
2. S. Sony, S. Laventure, and A. Sadhu, "A literature review of next-generation smart sensing technology in structural health monitoring," *Structural Control and Health Monitoring*, vol. 26, no. 3, Article ID e2321, 2021.
3. L. Sun, Z. Shang, Y. Xia, S. Bhowmick, and S. Nagarajaiah, "Review of bridge structural health monitoring aided by big data and artificial intelligence: from condition assessment to damage detection," *Journal of Structural Engineering*, vol. 146, no. 5, Article ID 04020073, 2021.
4. J. Liu, S. Chen, M. Bergés et al., "Diagnosis algorithms for indirect structural health monitoring of a bridge model via dimensionality reduction," *Mechanical Systems and Signal Processing*, vol. 136, Article ID 106454, 2020.
5. J. Liu, B. Chen, S. Chen, M. Bergés, J. Bielak, and H. Noh, "Damage-sensitive and domain-invariant feature extraction for vehicle-vibration-based bridge health monitoring," *IEEE*, 2020.
6. J. Liu, S. Xu, M. Bergés, and H. Y. Noh, "HierMUD: hierarchical multi-task unsupervised domain adaptation between bridges for drive-by damage diagnosis," *Structural Health Monitoring*, Article ID 147592172210811, 2022.

7. Shweta Pal, Kiran More, Priya Pise, "Content-Based Deduplication of Data Using Erasure Technique for RTO Cloud", 2018 International Conference on Advances in Communication and Computing Technology (ICACCT) Pages- 109-113
8. J. Liu, "Scalable bridge health monitoring using drive-by vehicles: PhD forum abstract," *ACM*, 2020.
9. J. Bernal Bernabe, J. L. Canovas, J. L. Hernandez-Ramos, R. Torres Moreno, and A. Sarmatia, "Privacy-preserving solutions for blockchain: review and challenges," IEEE Access, vol. 7, pp. 164908–164940, 2019. [8] J. Kolb, M. AbdelBaky, R. H. Katz, and D. E. Culler, "Core concepts, challenges, and future directions in blockchain," ACM Computing Surveys, vol. 53, no. 1, pp. 1–39, 2020.
10. D. Finfgeld-Connett, A Guide to Qualitative Meta-Synthesis, Routledge, New York, NY, 2018.
11. C. Romero, S. Ventura, M. Pechenizkiy, and R. Baker, *Handbook of educational data mining*, CRC Press, 20122
12. I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*, MIT Press, Cambridge, Mass, USA, 2016.
13. Prachi More, Shubham Chandugade, Shaikh Mohammad Shafi Rafiq, Priya Pise, "Hybrid Encryption Techniques for Secure Sharing of a Sensitive Data for Banking Systems Over Cloud ", 2018 International Conference on Advances in Communication and Computing Technology (ICACCT) Pages- 93-96
14. C. Romero and S. Ventura, "Educational data mining: a survey from 1995 to 2005," *Expert Systems with Applications*, vol. 33, no. 1, pp. 135–146, 2007.
15. C. Romero and S. Ventura, "Educational data mining: A review of the state of the art," *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, vol. 40, no. 6, pp. 601–618, 2010.
16. Priya Dudhale Pise, Nilesh J. Uke "Efficient Security Framework for Sensitive Data Sharing and Privacy Preserving on Big-Data and Cloud Platforms", International Conference on Internet of things and Cloud Computing March 2016Article No.: 38Pages 1–5https://doi.org/10.1145/2896387.2896423
17. C. Romero and S. Ventura, "Data mining in education," *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, vol. 3, no. 1, pp. 12–27, 2013.
18. R. S. Baker and Y. Yacef, "The state of educational data mining in 2009: A review and future visions," *JEDM-Journal of Educational Data Mining*, vol. 1, no. 1, pp. 3–17, 2009.
19. A. Peña-Ayala, "Educational data mining: A survey and a data mining-based analysis of recent works," *Expert Systems with Applications*, vol. 41, no. 4, pp. 1432–1462, 2014.
20. B. Bakhshinategh, O. R. Zaiane, S. ElAtia, and D. Ipperciel, "Educational data mining applications and tasks: A survey of the last 10 years," *Education and Information Technologies*, vol. 23, no. 1, pp. 537–553, 2018.
21. H. Aldowah, H. Al-Samarraie, and W. M. Fauzy, "Educational data mining and learning analytics for 21st century higher education: A review and synthesis," *Telematics and Informatics*, vol. 37, pp. 13–49, 2019.

22. C. Piech, J. Bassen, J. Huang et al., "Deep knowledge tracing," in *Annual Conference on Neural Information Processing Systems (NIPS)*, C. Cortes, N. D. Lawrence, D. D. Lee, M. Sugiyama, and R. Garnett, Eds., pp. 505–513, Curran Associates, Inc., 2015.