Visual Fingerprints of Vibration Signals Using Time Delay Embeddings

J. Rakuschek [1], A. Boesze [2], J. Schmidt [3], and T. Schreck[1]

[1] TU Graz, Institute of Visual Computing, Austria
[2] Binder+Co AG, Austria
[3] TU Wien, Institute of Visual Computing & Human-Centered Technology, Austria

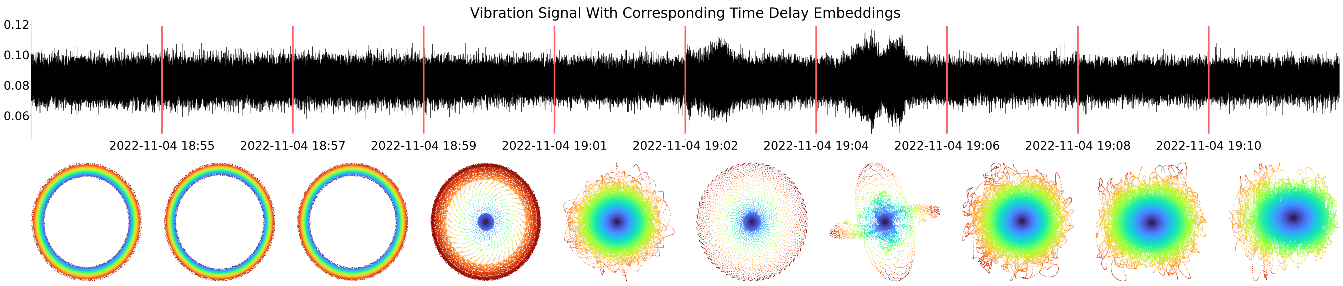

Figure 1: *Vibration measurements from a hydro power plant with the corresponding time delay embeddings per segment. The time delay embedding visualizations evolve over time and can be used as a fingerprint to highlight significant changes in the vibration data.*

Abstract

Most machines generate vibrations during operation, but effectively visualizing these vibrations is often a challenge, due to large and high-resolution data. Line charts suffer from overplotting, while frequency-domain analysis requires specialized knowledge in signal processing. We introduce a method that bridges the gap between time-domain and frequency-domain analysis: a visual fingerprint computed through the time delay embedding of the vibration data. This fingerprint helps identify segments exhibiting periodic behavior and can be used to cluster similar segments within a vibration signal. Additionally, we demonstrate its practical application in predictive maintenance, showcasing its potential for real-world industrial use.

CCS Concepts

• ***Human-centered computing*** $\rightarrow$ ***Visualization techniques;***

1. Introduction

The study of vibrations is essential for any mechanical engineering problem, as they are omnipresent: from simple motors to airplanes, any system with mass and elasticity has the potential to experience vibrations. While many vibrations are unavoidable and intrinsic properties of systems, they can be undesirable and may damage the machine. Furthermore, they may serve as indicators of whether a machine is functioning correctly. Therefore, conducting vibration analysis, typically performed in the frequency domain due to the oscillatory nature of vibrations, is essential for effective monitoring and maintenance strategies [GR21]. The spectrogram is one of the most common visualization techniques for the frequency domain, as it conveys changes in frequency over time and thus offers a visual interpretation of the frequencies. While analyzing frequencies is a natural step, Sujatha [Suj10] points out that the visual inspection of these signals in the time domain is still useful for capturing instantaneous or transient events. Although a significant fraction of information is hidden within the spectral content of the signal, the line chart can be used to quickly identify outliers and is more accessible to users with little background in the signal processing domain. Still, it is not possible to gauge from the line chart alone whether the signal is noise or a vibration. We aim to further enhance and complement the visual inspection in the time domain, enabling users to quickly gain an overview of different vibration profiles within the signal or to detect periodicity within noise. This is achieved through the use of *Time Delay Embeddings* (TDE), which provide an additional perspective by transforming the time series into a point cloud that can subsequently be projected

DOI: 10.2312/evs.20251094

onto a 2D plane. The key feature of the TDE is that periodicity within the signal results in elliptical structures and "round" point cloud shapes [PH13]. This property makes them useful as fingerprints for vibration signals such that groups of vibration patterns can be intuitively identified. Figure 1 provides an example which shows vibrations of a hydro power plant. Although these fingerprints are not meant to provide precise insights, they are useful to gain an overview, pointing users towards segments worth further analyzing. To further highlight the plausibility of our approach, we implement a clustering approach for TDEs to show that the signal is indeed split into meaningful segments.

2. Related Work

Although traditional techniques from vibration analysis are well established [GR21], Perea et al. [PH13] showed that methods from Topological Data Analysis (TDA), in particular the TDE, can offer deeper insights into signals and vibrations. The theoretical foundation for the TDE originates from studies on dynamic systems [Tak81] and has since been subject to extensive research, resulting in a rich theoretical basis [Per18, RC19, TH18, TAC*23, San18, HIB*21]. In recent work, Casolo et al. [CSZRS24] explored the use of TDEs for vibrations in wind turbine gearboxes and confirmed the useful property of circular patterns in the TDE that highlight vibrations. In this work, we demonstrate that the visual exploration of TDEs can provide meaningful insights.

The main issue with line charts for vibration signals is their lack of clarity due to overplotting [Kin10], as they represent dense time series with a vast number of data points. Ali et al. [AJXW18] proposed dimensionality reduction for generic time series as an additional perspective to gain an overview of clusters within the time series and to guide users toward points of interest in large time series. Ward and Guo [WG11] present an exploration approach for TDEs in which the authors focus on financial data, traffic flow, and ECG recordings. Each projected point is represented using a glyph that resembles the pattern shape at a given point in time. Furthermore, patterns can be selected based on regions of the projection, guiding users toward cyclic patterns, trends, and anomalies in the time series. Bernard et al. [BWS*12] extend this idea to multivariate time series, showing that paths in the projection correspond to patterns in the time series. While these approaches are reasonable exploration techniques for generic time series, vibration signals are not suitable since it is difficult to validate findings based on the accompanying line chart. Kumar et al. [KLK*05] present a method to construct bitmap thumbnails of time series using the Symbolic Aggregate Approximation representation. Although the fingerprints themselves are not meant to be interpreted, they provide an overview of patterns when viewed together. We also provide thumbnail visualizations (or fingerprints), in our case for vibration data, and show how they can be applied meaningfully.

3. Time Delay Embeddings as Fingerprints

Given a time series as a list of values, the Time Delay Embedding (TDE) is a sliding window view of the signal with window size w. Each window is subsequently interpreted as a point in high dimensional space $\mathbb{R}^w$, which effectively transforms the time series into a point cloud, hence the keyword *Embedding*. Due to space constraints, the precise mathematical definition is provided in the supplementary material. Since a TDE with $w > 3$ is difficult to visualize, we apply *Principal Component Analysis* (PCA) [Pea01] on the z-normalized TDE and retain the first two components. Thus, the TDE is projected onto a 2D plane, making it easier to visualize and explore. The PCA method was chosen due to its beneficial properties, such as linearity and the reasonable computational resources it requires compared to non-linear techniques. Furthermore, existing literature demonstrates that PCA is commonly used to visualize TDEs [CSZRS24, BJ19, WG11, BWS*12].

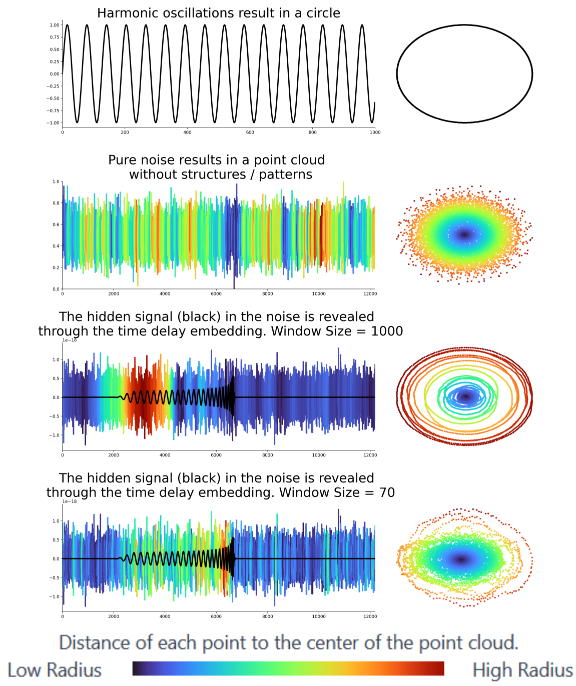

Figure 2: *Examples illustrating the time delay embedding concept. The coloring corresponds to the radius within the point cloud. The Turbo colormap is used to map the points from the cloud to the signal. The examples further highlight the effect of the window size, demonstrating the phenomenon of resulting circles when the window size aligns with the frequency.*

The resulting plot is the core concept of this work, as it is particularly well suited for vibration signals. Perea and Harer [PH13] showed in previous work that periodic structures within a signal lead to elliptic behavior in the point cloud. As discussed in section 1, vibrations inherently contain oscillations and thus quasi-periodic behavior, which is the reason for "round" projections. However, this does not apply to non-deterministic vibrations, as this type of vibration is inherently random. Figure 2 illustrates this idea with three examples: the first is a harmonic oscillation (a simple sine wave), resulting in a clear circle. The other two examples demonstrate the TDE on pure Gaussian noise and on noise with a "hidden" signal. In the latter two examples, the effect of the window size becomes evident: the elliptic behavior in the TDE emerges when the signal's frequency aligns with the window size. By as-

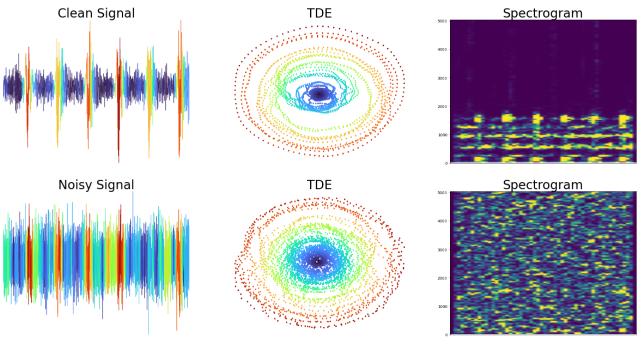

Figure 3: *Comparison between TDE and spectrogram for both clean and noisy engine signals. The noisy signal was created by adding Gaussian noise with a standard deviation of 2 to the original signal, demonstrating the TDE's applicability to noisy signals.*

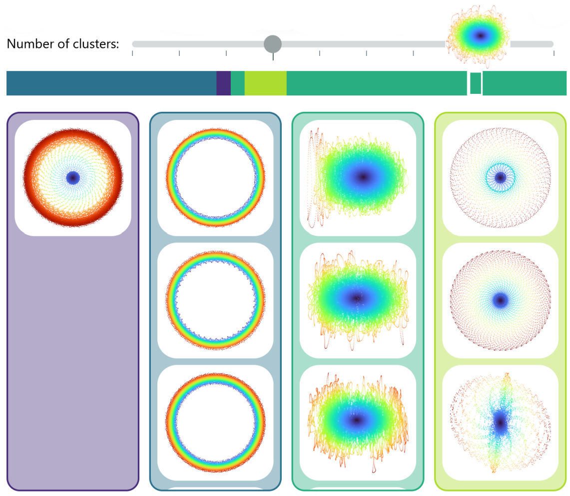

Figure 4: *The cluster view groups the TDEs based on the radius distribution within the point cloud. The clustering shows the separation of states within the hydro power plant, including the misfortune in the middle, which can be seen through the horizontal heat map that visualizes the cluster labels over time.*

signing colors to both the signal and the point cloud, a mapping from the periodic behavior in the signal to the structures in the projection can be observed. The circular patterns in the TDE necessitate coloring by radius (meaning the distance of each point to the center of the point cloud), as it enables the user to map annuli in the projection to segments in the vibration signal. In the following, we apply the *Turbo* rainbow coloring [Mik19] to color the TDE by radius. Although rainbow colormaps are often criticized for their poor characteristics, if well designed, they can be a valuable addition [WSSR23]. The *Turbo* rainbow coloring was chosen since it has the desired property of being perceptually uniform [Mik19]. Furthermore, the coloring is able to highlight the contrast between points close to the epicenter of the projection and points located on the border since blue and red are neighbors in the triadic color scheme. This is desirable since noise accumulates near the center while vibrations cause the circular patterns with a larger radius than noise. Figure 2 presents an example to illustrate this property and further justifies the desired contrast between center and border coloring. Finally, the Turbo coloring assigns green tones to points between center and border, thus completing the triadic scheme and enforcing a stark contrast between the three main segments.

However, in real data, vibrations may be occluded by noise, as seen in Figure 3. In the case of a clean vibration signal, the spectrogram clearly indicates the frequencies and the outer annuli in the TDE highlight high amplitudes. However, as noise is introduced to the original signal, the spectrogram and line chart lose their clarity and become less interpretable, whereas the circular patterns in the TDE persist even at high noise levels. The circular structures in the TDE therefore provide an indication to users of a hidden vibration within a noisy signal. Furthermore, the outer annuli still refer to the same locations in the signal as the noise level increases, demonstrating that the TDE is indeed referring to the same vibration patterns even in noisy environments.

While Perea and Harer [PH13] assert that circular structures manifest when the frequency aligns with the window size, we illustrate in Figure 5 that a sufficiently large window generally captures the signal's periodicity. Thus, we advise initiating analysis of a generic vibration signal with a large window size, as shown in Figure 5. The resulting TDE is a generic indicator for periodicity if round or circular structures are observed, however, for precise frequency analysis, a spectrogram remains the more suitable tool.

The insights presented in this section show that TDEs are valid visual fingerprints of vibration signals since they capture periodicity within the signal. Next, we further explore this idea by applying clustering to TDEs, which will highlight that TDEs are not only useful to detect periodicity, but also to emphasize change points within the signal.

4. Clustering TDEs of Vibration Signals

When searching for patterns or groups within a time series, clustering is a natural step, in particular to support many segments and long data. Figure 1 demonstrated that TDEs intuitively emphasize change points and result in diverse structures depending on the vibration profile. Since we assume that our data contains vibrations, we may conclude that the resulting TDE point clouds form a round structure; hence, we focus on radial properties of the point clouds to obtain features for clustering. Our resulting feature descriptor is the radius distribution in the form of a histogram, and to compute the similarities among them, any divergence measure for probability distributions can be used, for example the Jensen–Shannon divergence measure. Finally, we implement a hierarchical clustering method with complete linkage through an interactive prototype. In this case, the selection of the linkage method is not critical, as alternative methods such as average, group, or Ward's linkage produce results that are not significantly different. Therefore, a detailed discussion of the linkage method is excluded to maintain conciseness. The benefit of this agglomerative clustering is the resulting tree structure, which is only computed once. Whenever the user changes the number of clusters, they can be recursively retrieved from the tree, which is a computationally inexpensive operation;

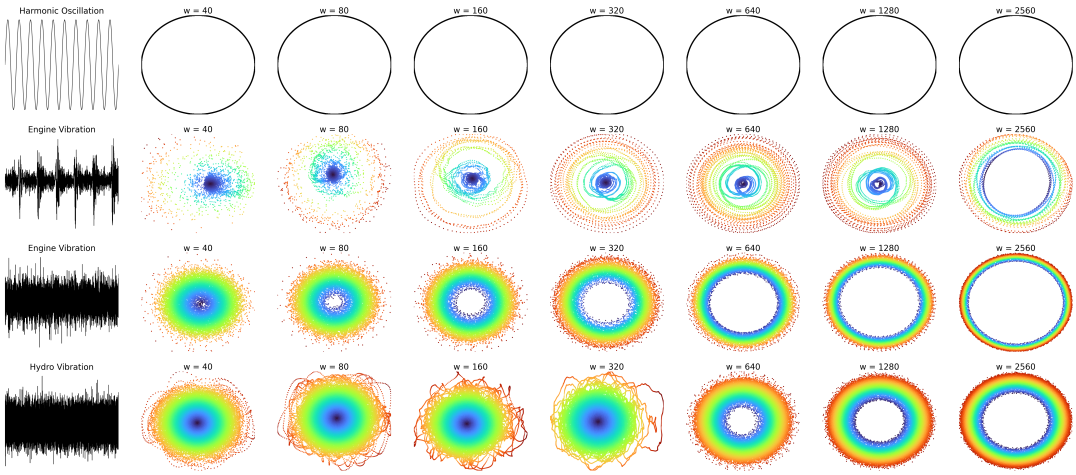

Figure 5: *We demonstrate the TDE on four datasets with different window sizes, which are doubled in each step. It can be observed that the TDE remains constant for the harmonic oscillation and converges in the case of noisy vibrations.*

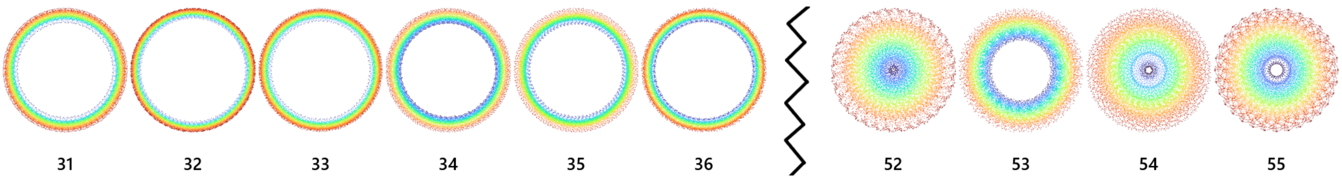

Figure 6: *The TDEs correspond to vibration segments in a run-to-failure scenario of an engine. It can be observed that the TDE stays constant in the beginning, but starts to attain a different shape as soon as engine wear becomes noticeable.*

hence, the user does not experience delay. Figure 4 demonstrates the proposed user interface to inspect the clusters. For chronologically ordered datasets, we offer a heat map in the form of a timeline, such that clusters can be mapped to specific time segments in the dataset. For instance, in Figure 4 one may observe the different states of the hydro power plant, which become apparent through the timeline.

5. Application to Predictive Maintenance

We applied the new TDE method to a real-world industry use case to demonstrate the technique's applicability for a predictive maintenance task. As shown in Figure 1, the TDE can highlight changes over time. Therefore, experts may use our technique to detect and inspect temporal data changes, like gradual or subtle anomalies. TDE conveys information about significant change points in the series. We applied TDE to a dataset of sensor recordings from machine operation. Domain experts needed to explore the data to see if it reflects certain machine states or changes over time. Figure 6 demonstrates this use case based on vibrations collected from an engine in which the engine runs until failure. At first, the TDE remains a stable circle with only minor noise artifacts. As soon as the engine experiences damage caused by wear, the vibration of the engine becomes noisy, which is reflected in the TDE. Again, this subtle noise addition is not visible through a line chart , but our TDE-based visual fingerprint helps to pinpoint the pattern.

6. Conclusion and Future Work

We presented TDE visualizations, as concise visual fingerprints of vibration signals for studying changes in high-frequency signal data. We demonstrated that TDEs can be used as a fingerprinting technique for vibration signals to effectively convey changes in the vibration profile and to detect periodicity. Based on our initial findings, we identified challenges which we need to address further.

Scalability issues need to be solved for making TDEs useable for large datasets. This refers to *Algorithm Scalability* according to the scalability in visualization model [RPA*24]. The computational expense, primarily due to the projection via PCA, presents a challenge. Another key finding highlights the **importance of the window size** used to compute TDEs. As demonstrated in Figure 2, the chosen window size significantly impacts the resulting TDE. In this work, the window size was manually selected for all datasets, which limits the exploration of diverse TDE representations. To address this, future research could introduce a parameter space exploration interface, enabling users to systematically compare different window sizes and identify the optimal configuration. While the fingerprinting technique for vibration signal seems plausible in our experiments, a rigorous **user study** is yet to be performed. The user study should be performed using the ICE-T procedure [WAM*19] such that the value of the visualization is appropriately evaluated. Further, we would be interested to acquire a taxonomy of fingerprints for a diverse set of vibration profiles.

Acknowledgment

The work by Julian Rakuschek and Tobias Schreck was partially funded by the Austrian Research Promotion Agency (FFG) within the framework of the flagship project ICT of the Future PRESENT, grant FO999899544.

References

[AJXW18] ALI M., JONES M. W., XIE X., WILLIAMS M.: Towards Visual Exploration of Large Temporal Datasets. *Proceeding of the International Symposium on Big Data Visual and Immersive Analytics* (Oct 17-19 2018), 1–9. doi:10.1109/BDVA.2018.8534025. 2

[BJ19] BRESTEN C., JUNG J.-H.: Detection of gravitational waves using topological data analysis and convolutional neural network: An improved approach. *arXiv abs/1910.08245* (2019). doi:10.48550/arXiv.1910.08245. 2

[BWS*12] BERNARD J., WILHELM N., SCHERER M., MAY T., SCHRECK T.: TimeSeriesPaths : Projection-Based Explorative Analysis of Multivariate Time Series Data. In *Proceedings of the 20th International Conference in Central Europe on Computer Graphics, Visualization and Computer Vision* (Plzen, Czech Republic, June 26-28 2012), vol. 20 of *WSCG '12*, pp. 97–106. doi:10.1594/pangaea.783598. 2

[CSZRS24] CASOLO S., STASIK A. J., ZHANG Z., RIEMER-SØRENSEN S.: Testing Topological Data Analysis for Condition Monitoring of Wind Turbines. In *Proceedings of the 8th European Conference of the Prognostics and Health Management Society* (Prague, Czech Republic, July 3-5 2024), vol. 8 of *PHME '24*, p. 10. doi:10.36001/phme.2024.v8i1.4117. 2

[GR21] GHAZALI M. H. M., RAHIMAN W.: Vibration Analysis for Machine Monitoring and Diagnosis: A Systematic Review. *Shock and Vibration* (2021). doi:10.1155/2021/9469318. 1, 2

[HIB*21] HIRSH S. M., ICHINAGA S. M., BRUNTON S. L., KUTZ J. N., BRUNTON B. W.: Structured time-delay models for dynamical systems with connections to Frenet–Serret frame. *Proceedings of the Royal Society A - Mathematical, Physical, and Engineering Sciences 477* (2021). doi:10.1098/rspa.2021.0097. 2

[Kin10] KINCAID R.: SignalLens: Focus+Context Applied to Electronic Time Series. *IEEE Transactions on Visualization and Computer Graphics 16* (2010), 900–907. doi:10.1109/TVCG.2010.193. 2

[KLK*05] KUMAR N., LOLLA V. N., KEOGH E. J., LONARDI S., RATANAMAHATANA C. A.: Time-series Bitmaps: a Practical Visualization Tool for Working with Large Time Series Databases. In *Proceedings of the 2005 SIAM International Conference on Data Mining* (Newport Beach, CA, USA, Apr 21-23 2005), SDM '05. doi:10.1137/1.9781611972757.55. 2

[Mik19] MIKHAILOV A.: Turbo, An Improved Rainbow Colormap for Visualization. http://research.google/blog/turbo-an-improved-rainbow-colormap-for-visualization/, Aug 2019. [Last accessed 2025-02-13]. 3

[Pea01] PEARSON K.: LIII. On lines and planes of closest fit to systems of points in space. *The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science 2*, 11 (1901), 559–572. doi:10.1080/14786440109462720. 2

[Per18] PEREA J. A.: Topological Time Series Analysis. *Notices of the American Mathematical Society 66* (2018). doi:10.1090/NOTI1869. 2

[PH13] PEREA J. A., HARER J.: Sliding Windows and Persistence: An Application of Topological Methods to Signal Analysis. *Foundations of Computational Mathematics 15* (2013), 799–838. doi:10.1007/s10208-014-9206-z. 2, 3

[RC19] RAVISHANKER N., CHEN R.: Topological Data Analysis (TDA) for Time Series. *arXiv: Applications* (2019). doi:10.48550/arXiv.1909.10604. 2

[RPA*24] RICHER G., PISTER A., ABDELAAL M., FEKETE J.-D., SEDLMAIR M., WEISKOPF D.: Scalability in Visualization. *IEEE Transactions on Visualization and Computer Graphics 30*, 7 (2024), 3314–3330. doi:10.1109/TVCG.2022.3231230. 4

[San18] SANDERSON N. F.: *Topological Data Analyses of Time Series Using Witness Complexes*. PhD thesis, University of Colorado, 2018. URL: https://core.ac.uk/download/593675023.pdf. 2

[Suj10] SUJATHA C.: *Vibration and acoustics: Measurement and Signal Analysis*. McGraw-Hill Education LLC, 2010. 1

[TAC*23] TAN E., ALGAR S. D., CORRÊA D. C., SMALL M., STEMLER T., WALKER D. M.: Selecting embedding delays: An overview of embedding techniques and a new method using persistent homology. *Chaos - An Interdisciplinary Journal of Nonlinear Science 33* (2023), 032101. doi:10.1063/5.0137223. 2

[Tak81] TAKENS F.: Detecting strange attractors in turbulence. In *Proceedings of the Symposium on Dynamical Systems and Turbulence* (Warwick, UK, 1981). doi:10.1007/BFB0091924. 2

[TH18] TRAN Q. H., HASEGAWA Y.: Topological time-series analysis with delay-variant embedding. *Physical Review E 99* (2018), 032209. doi:10.1103/PhysRevE.99.032209. 2

[WAM*19] WALL E., AGNIHOTRI M., MATZEN L. E., DIVIS K. M., HAASS M. J., ENDERT A., STASKO J.: A Heuristic Approach to Value-Driven Evaluation of Visualizations. *IEEE Transactions on Visualization and Computer Graphics 25* (2019), 491–500. doi:10.1109/tvcg.2018.2865146. 4

[WG11] WARD M., GUO Z.: Visual Exploration of Time-Series Data with Shape Space Projections. *Computer Graphics Forum 30* (2011), 701–710. doi:10.1111/j.1467-8659.2011.01919.x. 2

[WSSR23] WARE C., STONE M. C., SZAFIR D. A., RHYNE T.-M.: Rainbow Colormaps Are Not All Bad. *IEEE Computer Graphics and Applications 43* (2023), 88–93. doi:10.1109/MCG.2023.3246111. 3