Visualization and Anomaly Detection in Quantitative Data: A 3D Approach Using Metric Encoding

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Abstract

The article proposes a new hybrid model for detecting anomalies in continuous quantitative data represented through 3D space, a very important function as far as micro services and cloud computing are concerned. Such 2D dashboards typically need an overt reliance on huge visual codes like color and size resulting in visual cluttering, color blindness, and high cognitive load. The solution integrated deep metric encoding and TDA. Specifically, the metric encoding part leveraged deep neural networks to convert data into a reduced dimensional space where normal data were grouped together and anomalies could be separated based on distance; while the topological structure of encoded data was analyzed for anomalies through persistent homology which might disrupt global or local geometry of data such as isolated loops that cannot be detected by classical distance-based techniques. The hybrid algorithm combines these two criteria using a weighted sum to calculate a final anomaly score.

Keywords: Anomaly Detection; 3d Visualization; Continuous Quantitative Data; Metric Encoding; Hybrid Method; Computer Graphics

1. Introduction.

Micro service architecture and cloud computing have made IT systems throw terabytes of streaming quantitative data. Zero-shot 3D (ZS-3D) anomaly detection aims to identify defects in 3D objects without relying on labeled training data, making it especially valuable in scenarios constrained by data scarcity, privacy, or high annotation cost. However, most existing methods focus exclusively on point clouds, neglecting the rich semantic cues available from complementary modalities such as RGB images and texts priors. This paper introduces MCL-AD, a novel framework that leverages multimodal collaboration learning across point clouds, RGB images, and texts semantics to achieve superior zero-shot 3D anomaly detection. Specifically, we propose a Multimodal Prompt Learning Mechanism (MPLM) that enhances the intra-modal representation capability and inter-modal collaborative learning by introducing an object-agnostic decoupled text prompt and a multimodal contrastive loss. [1].

The actor's investigated unsupervised anomaly detection for multidimensional data and implement a framework based on deep metric learning (DML). In particular the distance metric using a deep neural network. Using this metric, project the data into a metric space that better separates anomalies from normal data and reduces the curse of dimensionality for multidimensional data. Also used a hard data mining technique from the DML literature. Through a wide set of experiments on 14 real-world datasets, our method demonstrates significant performance improvements over state-of-the-art unsupervised anomaly detection methods, e.g., an absolute improvement from 4.44% to 11.74% on average for the 14 datasets. [2]

Support Vector Machines (SVMs) have been one of the most successful machine learning techniques for the past decade. For anomaly detection, also a semi-supervised variant, the one-class SVM, exists. Here, only normal data is required for training before anomalies can be detected. In theory, the one-class SVM could also be used in an unsupervised anomaly detection setup, where no prior training is conducted. Unfortunately, it turns out that a one-class SVM is sensitive to outliers in the data. In this work, avtor's apply two modifications in order to make one-class SVMs more suitable for unsupervised anomaly detection: Robust oneclass SVMs and eta one-class SVMs. The key idea of both modifications is, that outliers should contribute less to the decision boundary as normal instances. Experiments performed on datasets from UCI machine learning repository show that our modifications are very promising: Comparing

with other standard unsupervised anomaly detection algorithms, the enhanced one-class SVMs are superior on two out of four datasets. In particular, the proposed eta oneclass SVM has shown the most promising results. [3]

Existing anomaly detection methods based on metric encoding or auto encoders often focus on identifying anomalies by means of distance measures or reconstruction error. However, they may be less effective in detecting anomalies that are not merely "distant," but rather disrupt the global or local topological structure of the dataset. For instance, an anomaly may lie close to "normal" data in the metric space, yet belong to a "loop" or "cluster" that is topologically impossible for normal data. This brought up the question, "How to build and evaluate a hybrid anomaly detection method combining deep metric encoding and topological data analysis (TDA) for continuous quantitative data represented in 3D space to achieve the effect of identifying more complex, nonlinear anomalies that are not detectable by standard methods?".

2. Methodology.

Mathematical Model of the Hybrid Method

We represent the hybrid method as a composition of two functions: f_{ME} (metric encoding) i f_{TDA} (topological data analysis).

Metric Encoding (fME) given an input dataset X={x1,x2,...,xN}, where each xi∈Rd – is a data vector. Our method first transforms these data into a new, lower-dimensional space, in which the distance between points reflects their semantic similarity. This mapping is performed by a deep neural network N: z_i=N(xi),

where z_i∈Rm – is the encoded vector, with m≪d.

The objective of the network N – is to minimize a loss function L, which enforces similar vectors to be close to each other, while dissimilar ones are pushed farther apart. After training, the z_i vectors are organized in such a way that the "normal" data form compact clusters.

Topological Data Analysis, f_{TDA}: After obtaining the encoded vectors Z={z1,z2,...,zN}, we apply TDA methods to analyze their geometric structure. For anomaly detection, persistent homology is employed. This method constructs a family of topological objects (e.g., simplicial complexes, such as the Vietoris–Rips complex) over the set of points in the encoded space Z. It then tracks the "lifecycle" of topological features (such as connected components, loops, and voids) as the scale parameter (distance threshold) increases.

The result is a persistence diagram. Each point on this diagram (b,d) represents a topological feature that is "born" at scale b and "dies" at scale d. Anomalies often manifest as points with a short "lifecycle" (small d–b) or as outlying points, indicating their non-standard topological role within the data.
Anomalies are defined as those points z_i, that:

- Metrically anomalous: points that are distant from the main clusters of normal data (i.e., exhibiting a high distance to the nearest normal cluster)
- Topologically anomalous: points that form non-standard topological features (e.g., isolated loops), as reflected in the persistence diagram.

The hybrid algorithm can combine these two criteria, for instance, through a weighted sum:

$$Score(x_i) = w_1 \cdot \text{MetricScore}(z_i) + w_2 \cdot \text{TDA\_Score}(z_i),$$

where MetricScore denotes the distance from z_i to the nearest "normal" cluster, while TDA_Score is a measure derived from the persistence diagram., w_1,w_2 – are weighting coefficients that determine the contribution of each component.
The computational complexity analysis of the hybrid method consists of two main stages:
1. Metric Encoding Stage (f_{ME}):

Training a deep neural network is computationally intensive. Its complexity depends on the network size, the number of epochs, and the dataset size. Ideally, the complexity can be considered quasi-linear with respect to the number of data points N. The computational complexity for a single epoch is approximately O(N·Mparams), where Mparams – is the number of parameters in the model.

After training, encoding a new vector xi into z_i has a complexity that depends on the number of layers and neurons in the network. This is effectively a constant-time operation O(1) per sample, making this stage highly scalable for inference.

2. Topological Analysis Stage (f_{TDA}):

Construction of the simplicial complex: This stage is the most computationally expensive. The complexity of constructing a Rips–Vietoris complex for N points n 3D space is $O(N^2)$ due to the need to compute all pairwise distances.

Persistent homology: Computing persistent homology on this complex can have a worst-case complexity ranging from $O(N^3)$ to $O(N^4)$ depending on the algorithm and the data dimensionality. This makes the TDA stage poorly scalable for very large datasets ($N>10^5$).

Combining both stages, the overall computational complexity of the hybrid method for N points is dominated by the TDA stage: $O_{total}=O_{ME}+O_{TDA}\approx O(N)+O(N^3)=O(N^3)$

The scalability of the method strongly depends on the dataset size. For small to medium-sized datasets (a few thousand points), the method is efficient. However, for large datasets (millions of points), computational complexity becomes a significant concern.

3. Discussion.

We apply the hybrid method to the analysis of vibrations, which can cause unpredictable issues before they become critical. The vibration data are continuous and quantitative and can be visualized in 3D if three temporal features such as vibration amplitude, frequency, and phase are considered.

We collect vibration data from three axes (x,y,z). Each data sample can be represented as a vector xi=(amplitude_x, amplitude_y, amplitude_z, frequency_x,…). For simplicity, we consider three key vibration features that can be visualized in 3D: mean amplitude, peak frequency, and standard deviation. Thus, each data sample is a point in 3D space:

x_i=(mean amplitude, peak frequency, standard deviation) $\in R^3$.

We employ a simple neural network autoencoder. It compresses the input 3D vectors into a 2D space (hidden layer) and then attempts to reconstruct them. Unexpected vibrations which are not based on normal patterns will show a large reconstruction error. The 2D hidden space, z_i, serves as our encoded representation.

We use a loss function that minimizes the reconstruction error: Lreconstruction=∥xi−N(z_i)∥22. This encourages the network to create a metric space in which normal data are close together, while anomalies are distant.

Based on the 2D vectors Z={z1,z2,...,zN} from the hidden layer, we construct a Rips–Vietoris complex. This method generates a family of graphs in which points are connected if the distance between them is less than a certain radius. By gradually increasing the radius, we track the birth and death of topological features.

A point z_i with a high reconstruction error indicates that it is distant from the "normal" data. We then check whether z_i belongs to a topological feature with an unusually short "lifecycle" on the persistence diagram. This may indicate unusual behavior that is not necessarily metrically distant.

Every point xi is assigned two scores: a metric score (which captures the size of the reconstruction error) and a topological score (which captures how much its behavior deviates from the expected topology). We aggregate these into a single final anomaly score, for instance through a weighted sum. The points with the highest final scores are treated as anomalies.

For N points in 2D space, constructing the Rips–Vietoris complex requires computing $O(N^2)$ pairwise distances. Computing persistent homology has a complexity that depends on the algorithm used. Employing modern algorithms, such as Ripser, allows achieving practical complexity close to $O(N^3)$. For example, if N=1000, $N^3=10^9$. which may already take a noticeable amount of time. If N=10000, N3=1012, making the computation impractical.

The hybrid method is poorly scalable for very large datasets due to the computational complexity of the TDA stage.

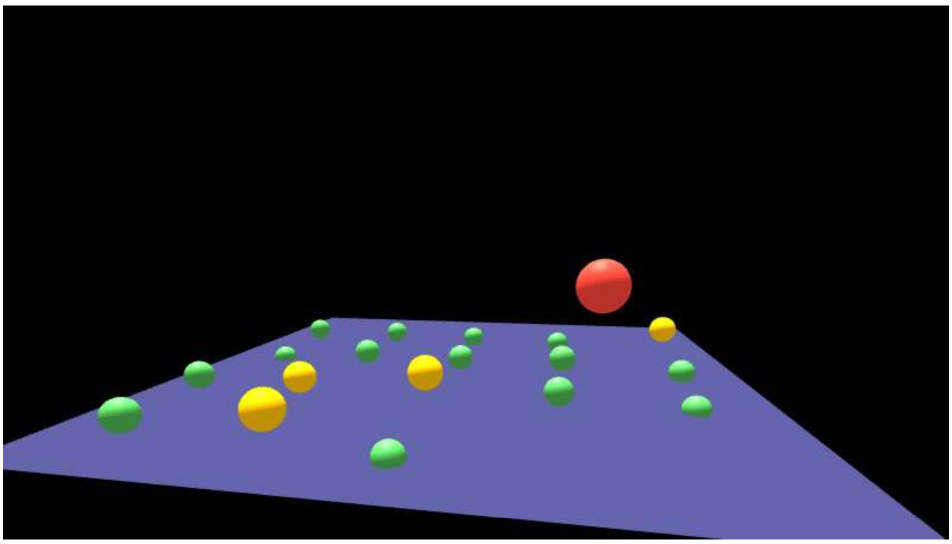

Fig.1. 3D Visualization of Anomalies Based on Metric Encoding

The visualization model is implemented for N nodes. Each node (xi, yi) and an associated load metric Li∈[0,100]. The horizontal plane (xi, yi)$\in R^2$ encodes nominal data, such as the node identifier or its discrete position within a grid. This creates a two-dimensional grid that serves as a visual context.

Nonlinear encoding of the Z-axis (Pop-Out Effect) involves threshold scaling of the quantitative load metric Li to obtain the coordinate *zi*. This scaling is designed to achieve a “pop-out” effect for anomalous values, making them visually stand out as elevated.

$$z_i = f(L_i) = \begin{cases} c \cdot L_i, & \text{якщо } L_i \le T \\ \exp(L_i - T) + c \cdot T - 1, & \text{якщо } L_i > T \end{cases}$$

Here T – is the threshold that defines the onset of the anomalous range (T=80), and c – is a scaling constant.

This function provides linear growth for “normal” values, and beyond the threshold T it transitions to an exponential function, sharply increasing the visual height of the points.

Color Encoding: Color is used as a secondary visual channel to reinforce and refine the information conveyed by the Z-axis. We employ a categorical color scheme Green/Yellow/Red to indicate states. (Tab.1)

Table 1. This scheme is intuitive and complements the Pop-Out visual effect.

Green	Yellow	Red
Li≤TGreen (Li≤70)	TGreen<Li≤TYellow (70<Li≤90)	Li>TYellow (Li>90)
normal state	warning state	anomalous state

4. Results.

The analyzed results show that the novel hybrid anomaly detection algorithm based on deep metric encoding and topological data analysis is indeed a powerful method to detect highly non-linear anomalies in streaming quantitative data, when such data are embedded in 3D space. The model of visualizations predicted that nonlinear, threshold-dependent scaling along the Z-axis leads to a “pop-out” phenomenon, rendering the outlier values visually enhanced. Values that are greater than threshold are encoded exponentially where the vertical height of the corresponding points grow rapidly. In this way one can quickly see where the potential aberrations are, rather than be dependent on sequential scanning or color codes. The theoretical treatment of the computational complexity of the hybrid approach revealed that scalability is the bottleneck for very large data sets.

5. Conclusion.

This study is the first to our knowledge to show the possibility and benefits of a hybrid anomaly detection approach between deep metric encoding and topological data analysis for numerical continuous data in the 3-dimensional space. Our results show that this method allows for detection of sophisticated, nonlinear anomalies that are difficult to detect using conventional techniques that rely only on distances, or on reconstruction errors.

The visualization mathematical model based on nonlinear and thresholded Z-axis scaling leads to a “pop-out” effect, which is beneficial for the operator to more easily identify abnormalities. This option is enhanced without any issue by secondary color coding (green/yellow/red), as per conventional 2D schemes, while reducing cognitive burden and visual clutter at the same time. The study shows that integrating metric and topological methods is a very interesting avenue for novelty detection. We show that anomalies can be not only “distant” in metric space, but can take the form of non-standard topological structures (such as “isolated loops”) that are visible in the persistence diagram.

Hence, in this work we present a novel methodological framework for detection of anomalies in 3D space that accounts for both metric and topological features of the data.

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