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Intelligent Data Fusion for Anomaly Detection in Dutch Railway Catenary Condition Monitoring

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Abstract

Aiming to handle the increasing variety and volume of railway infrastructure monitoring data, this paper explores the use of intelligent data fusion methods for automatic anomaly detection of railway catenaries. Three classical data dimensionality reduction methods, namely the principal component analysis (PCA), the autoencoder neural network, and the t-distributed stochastic neighbor embedding (t-SNE) are adopted for the data fusion of catenary monitoring data. Then, anomaly detection can be achieved using new features that are automatically extracted from the original data, which requires no prior knowledge of the data or catenary conditions. A case study using data measured from the Dutch railway is presented to compare the performance of the three methods. Six types of catenary monitoring data, including pantograph-catenary contact force, pantograph-catenary friction force, contact wire thickness, contact wire height and stagger, are used in the presented case study. It is demonstrated that both PCA and autoencoder can detect anomalies from catenary monitoring data, while t-SNE shows little indication of such ability. Further, the autoencoder outperforms PCA in distinguishing anomalies in the case study, likely owing to its superiority in analysing data with nonlinearity. Overall, autoencoder is a promising technique for automating the anomaly detection of railway catenaries. The detection results can provide indicators for failure prediction and maintenance decision making.

Keywords: railway catenary, condition monitoring, anomaly detection, data fusion.

1. Introduction

Catenary systems or overhead contact lines are a critical infrastructure type in electrified railways. Moving trains collect power from catenary systems through the sliding contact with one or multiple pantographs mounted on the train roof. Failures of a catenary system, such as broken contact wires, can cause disruptions to train services and even damages to infrastructures and trains. It is thus necessary to prevent the occurrence of catenary failures, which can consequently save costs of reactive maintenance and prolong the life cycle of existing infrastructures [1].

Condition monitoring is nowadays commonly used by worldwide railway infrastructure managers for preventing failures. Perceiving early signs of failures through condition monitoring can enable predictive maintenances that restore the infrastructure condition to an acceptable level ahead of potential failures. For railway catenaries, various monitoring techniques have been developed and applied in recent years [2]. These techniques mainly include measurements of forces [3], positions [4], vibrations [5], images and videos in 2D [6] or 3D [7]. As a result, the data variety, volume, veracity, velocity and value, known as 5Vs of big data, in catenary condition monitoring have been rapidly increasing in recent years. This brings opportunities as well as challenges in data utilization that should provide actionable information for maintenance decision making.

One of the challenges for catenary condition monitoring is dealing with the growing data variety measured by heterogeneous sensors. Although different types of data can indicate the catenary condition individually, the fusion of multiple data types may provide richer information and more accurate diagnoses on the catenary condition. The benefit of data fusion for railway infrastructure has been demonstrated by several studies [8-10]. Another challenge is brought by the increasing data volume. This entails the need for algorithms that automatically process a large amount of data while capturing anomalies that are not yet known or defined in practice. Therefore, approaches that can properly handle both the variety and volume of data are desired.

This study aims to propose an intelligent data fusion method that can automatically detect anomalies using heterogeneous data sources from catenary monitoring. Three mainstream methods for anomaly detection, namely the principal component analysis (PCA) [11], the autoencoder neural network [12], and the t-distributed stochastic neighbor embedding (t-SNE) [13], are adopted and tested on catenary monitoring data. A case study using data measured in the Dutch railway is presented to demonstrate the performance and effectiveness of the three methods. The rest of the paper is organized as follows. Section 2 briefly introduces the theory of the three anomalies detection methods. Section 3 proposes an approach to perform catenary anomaly detection for improving failure prevention and maintenance decision making. Section 4 presents the case study using data from the Dutch railway and discusses the results. Section 5 concludes this paper.

2. Anomaly Detection Methods

This section briefly introduces PCA, autoencoders, and t-SNE that are adopted in this study for anomaly detection of catenary systems. These methods do not require prior knowledge of catenary physical conditions and data types, thus can be directly implemented for data with large variety and volume. Applicabilities of the three methods are discussed in short. Note that data normalization is first carried out for each data type so that all data are on the same scale and treated as equally important by the three methods.

2.1 PCA

PCA is a classical method for data dimensionality reduction and fusion. It is a non-parametric method that extracts relevant features or information from data sets. It reduces the data dimensionality by linearly projecting data points onto some principal components to obtain lower-dimensional data while preserving the variation of the original higher-dimensional data. Given a normalized $m \times n$ data matrix $\mathbf{Z}$ where m is the total number of data samples and n is the number of different data types, the standard PCA algorithm consists of three steps, including computing the covariance matrix of $\mathbf{Z}$, calculating the eigenvectors and eigenvalues of the covariance matrix, and identifying principal components. For an elaborated introduction of PCA, one can refer to [11].

PCA is suitable for transforming data that are linearly correlated into a lower dimension where all dimensions of the data are linearly uncorrelated. This implies that nonlinearly correlated data cannot be properly analysed by PCA. Notably, catenary monitoring data, especially dynamic data measured under the interaction with a pantograph, have certain nonlinearities associated with different data types.

2.2 Autoencoders

Autoencoders are a type of neural network that can achieve unsupervised dimensionality reduction of data. An autoencoder takes the input training data set $\mathbf{x} = \{x_1, x_2, ..., x_n\}$ and maps it into a hidden representation $\mathbf{h} = \{h_1, h_2, ..., h_l\}$ through an activation function

$$\mathbf{h} = \varphi(\mathbf{W}\mathbf{x} + \mathbf{b}) \tag{1}$$

where $\mathbf{W}$ and $\mathbf{b}$ are the weights and bias terms to be trained and learned in the autoencoder. Then, the hidden representation $\mathbf{h}$ is mapped into an output representation $\mathbf{y} = \{y_1, y_2, ..., y_n\}$, aiming to approximate $\mathbf{x}$ so that $\mathbf{y} \approx \mathbf{x}$. When $l < n$, the hidden representation $\mathbf{h}$ becomes a lower-dimensional version of the input $\mathbf{x}$. In other words, the n-dimensional input $\mathbf{x}$ is compressed into a lower-dimensional representation $\mathbf{h}$, which can reconstruct the input using compressed data.

Autoencoders can reduce data dimensionality via nonlinear transforms when the activation function is nonlinear. Therefore, it is suitable for fusing data measured from nonlinear systems, such as pantograph-catenary systems.

2.3 t-SNE

As a classical nonlinear dimensionality reduction method, t-SNE is widely used for visualizing high-dimensional data in a space of two or three dimensions. It can reveal nonlinear correlations in a dataset by first constructing a probability distribution in which similar high-dimensional data are assigned with a higher probability. Then, a similar probability distribution in two or three dimensions is defined by minimizing the Kullback–Leibler divergence between the two distributions using gradient descent. In such a way, the resulting 2D or 3D map reflects the similarities between the high-dimensional data, which can be used for the anomaly detection of catenary that involves data dominated by normal or healthy samples. For a step by step implementation of t-SNE, one can refer to [13].

t-SNE is also suitable for analyzing data with inherent nonlinearity, making it a good candidate for identifying anomalies in catenary monitoring data. When the analysed data dimension is much larger than the targeted two or three dimensions, it is advised to first reduce the dimensionality of data before applying t-SNE.

3. Anomaly Detection for Failure Prevention and Maintenance

In railway infrastructures, not all failures of infrastructures are well defined and perceived from monitoring data. Anomaly detection tells problems from data regardless of the corresponding failure modes, which will not overlook any potential infrastructure failures. In this study, we adopt anomaly detection methods to integrate multiple types of catenary monitoring data into key performance indicators (KPIs). As a result, anomalies at different data locations can be identified based on the KPIs. The identified anomalies provide input for estimating the failure rate and criticality in Failure Mode Effects and Criticality Analysis (FMECA) [14], which ultimately enables better maintenance decision making for catenary systems.

Figure 1 summarizes the framework of the proposed approach and its relationship with FMECA and maintenance. In the proposed approach, we consider multiple types of data measured in catenary systems. Concretely, these data include six types of data for the Dutch railway, namely pantograph-catenary contact force, pantograph-catenary friction force, contact wire maximum and minimum thickness, contact wire height and stagger, where the maximum and minimum thickness denote the minimum and maximum wire thickness measured within one sampling interval, respectively. Since all anomaly detection methods adopted in this approach are essentially unsupervised, one can include as many as possible data types that are relevant for reflecting catenary conditions. Also, it should be noted that the extracted KPIs may not have physical meanings because they are generated by fusing the input data into abstract features at a lower dimension. Such physical meanings should be interpreted together with the input data.

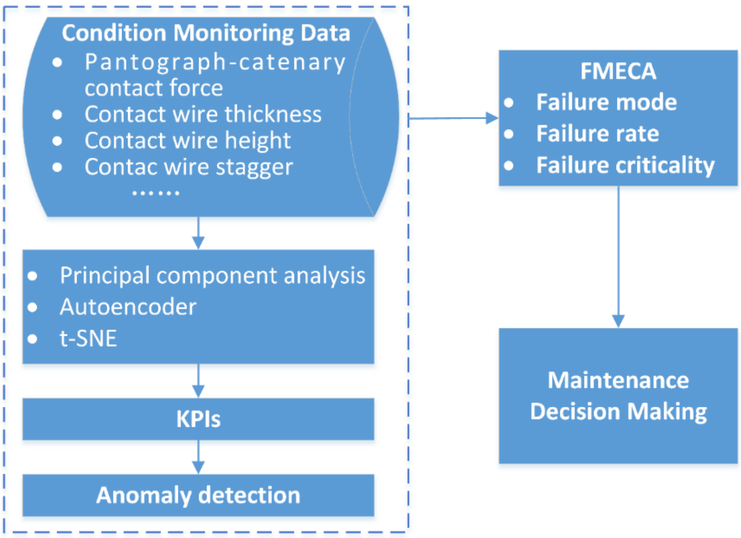


Figure 1: Framework of the proposed approach and its relationship with FMECA and maintenance.

4. A Case Study in the Dutch Railway

A typical catenary monitoring dataset measured in the Dutch railway is shown in Figure 2. The data sampling interval is 0.25 m. For the thickness, height, and stagger of contact wires, there are two sets of data for two wires since a pair of contact wires are used in the measured railway line. Note that the contact wire heights are relative values compared with nominal values.

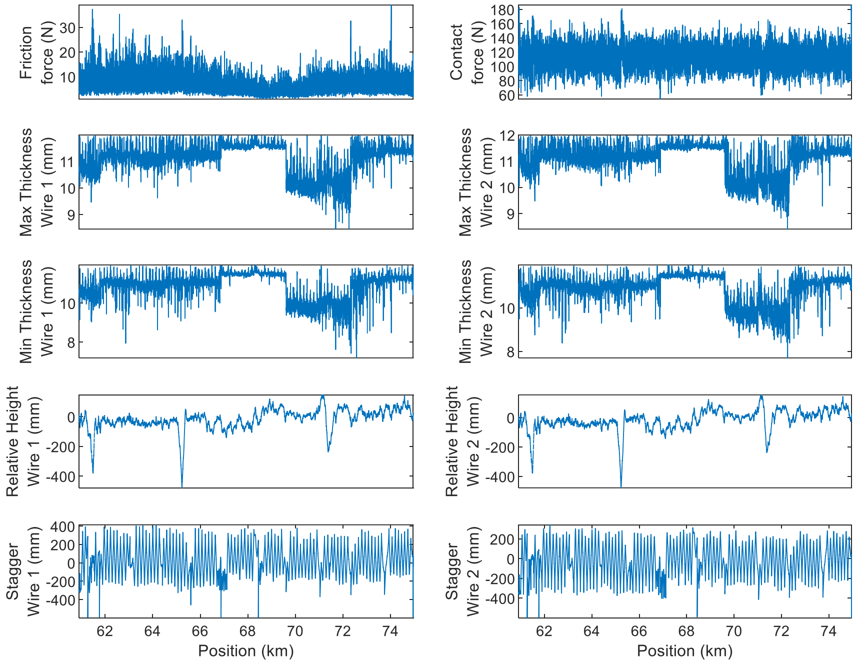
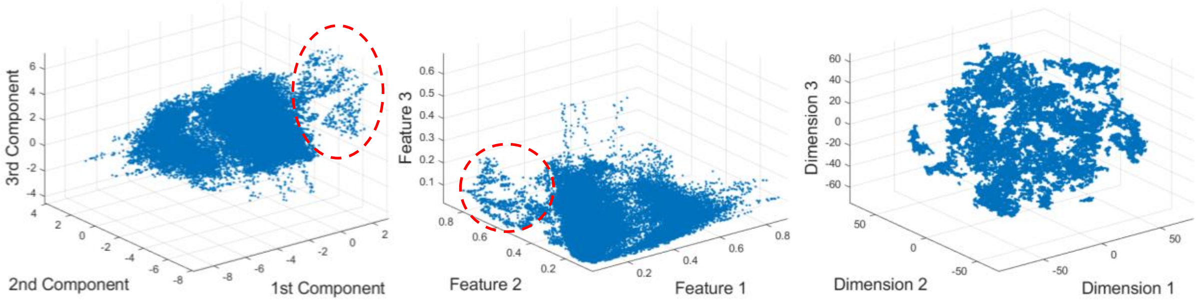


Figure 2: The dataset used for catenary anomaly detection.

For fusion of the input data, a unified target dimension of three is used for the adopted three methods, considering that the input data mainly reflect the catenary condition in three directions which are vertical to the ground, lateral to and longitudinal along the track. For anomaly detection using the three methods, this means that the first three principal components from PCA are used, the hidden representation has three dimensions in the autoencoder, and a 3D map is generated by t-SNE.

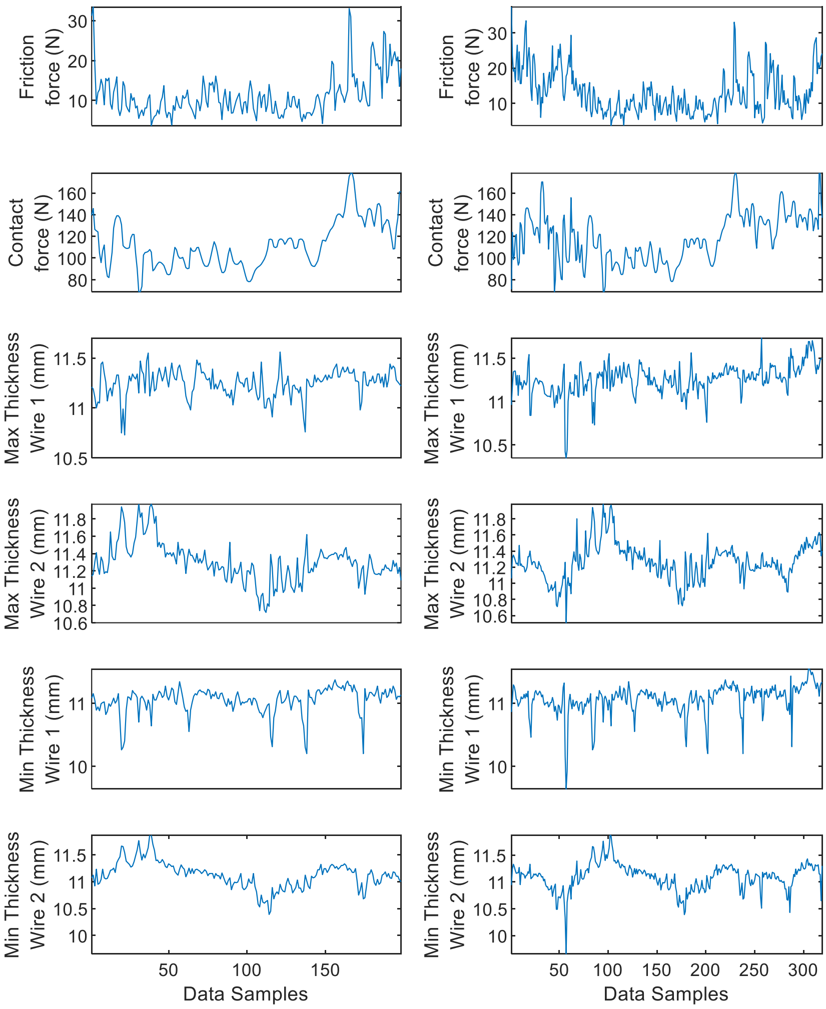


(a) PCA (b) Autoencoder (c) t-SNE

Figure 3: Data fusion results using the three methods for dimensionality reduction.

Figure 3 shows the resulting 3D feature space generated by the three methods. In the result of PCA, the first three principal components explain about 79 percent of the total input data variance, which justifies the selection of three dimensions for dimensionality reduction. From Figure 3(a), it can be seen that there is a clear gathering of a majority of data points while some abnormal data are distinguishable from the majority, as highlighted by a red dashed-line circle. Similarly, such a pattern can be also observed in the result of an autoencoder in Figure 3(b). Some outliers, like the ones circled by a dashed line, are located further away from the majority of data in the feature space. However, the result of t-SNE does not share the same pattern as the former two methods. The data points are scattered over the feature space, making it difficult to distinguish between normal and abnormal samples. In summary, two methods, namely PCA and autoencoder, demonstrate the potential in detecting anomalies from catenary monitoring data, while t-SNE show little indication of anomalies in the adopted data.

To further validate if the abnormal data points indicated by the results of PCA and autoencoder are in fact anomalies, the corresponding monitoring data can be examined. Figure 4 shows the data samples that are located relatively further from the majority in the circled data points from Figures 3(a) and 3(b). Data of height and stagger are omitted for simplicity. It can be seen both methods manage to identify some extrema in the measurement data. However, the anomalies identified by the autoencoder have even larger or smaller data values since the plots are using the same scale in the vertical axis. This is particularly obvious in the case of the thicknesses of the two wires. Such differences imply the better suitability of autoencoders for analysing catenary monitoring data that have certain nonlinearities.



(a) PCA (b) Autoencoder

Figure 4: Data with anomalies detected by PCA and autoencoder.

5. Conclusions

As an attempt to tackle the challenges brought by the growing variety and volume of railway infrastructure monitoring data, this paper presents preliminary results on using data fusion methods to achieve automatic anomaly detection of railway catenary systems. Three data fusion methods including PCA, autoencoder neural network, and t-SNE, are adopted and tested on real-life data measured in the Dutch railways. Performances of the three methods are presented and qualitatively compared. It is found that both autoencoder and PCA can achieve catenary anomaly detection by fusing multiple types of catenary monitoring data, while the autoencoder is superior owing to its ability in handling data with nonlinearity.

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