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Research Article

Autoencoder with Gramian Angular Summation Field for Anomaly Detection in Multivariate Time Series Data

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ABSTRACT

Uncertainty is ubiquitous in data and constitutes a challenge in real-life data analysis applications. To deal with this challenge, we propose a novel method for detecting anomalies in time series data based on the Autoencoder method, which encodes a multivariate time series as images by means of the Gramian Angular Summation Field (GASF). Multivariate time series data is represented as 2D image data to enhance the performance of anomaly detection. The proposed method is validated with four time-series data sets. Experimental results show that our proposed method can improve validity and accuracy on all criteria. Therefore, effective anomaly detection in multivariate time series data can be achieved by combining the methods of Autoencoder and Gramian Angular Summation Field.

1. Introduction

Anomaly detection involves discovering unusual patterns in time series data. Such detection is an important and challenging task, widely applied in various fields, such as credit card processing, medical diagnosis, sensor network operations, intrusion detection, and other areas [1]. Many algorithms have been developed to detect anomalies, but most of them are limited to analysis of univariate time series.

Recently, deep learning techniques have been applied to anomaly detection, the most common being Principal Component Analysis (PCA), which is a linear dimensionality reduction technique. PCA projects high-dimensional time series into a low-dimensional sequence. However, PCA is not flexible and cannot perform non-linear operations. A newer dimensionality reduction method is autoencoder [2], [3], which has become a popular method for anomaly detection. Autoencoder is used to perform dimension reduction by stacking up layers to form a deep autoencoder. The hidden units are expected to extract features that represent the data faithfully by reducing the number of units in the hidden layer. Autoencoder judges whether something is abnormal by considering the difference between encoded data and the original [4], [5], Moreover, the autoencoder can perform both linear and non-linear operations [6].

In this paper, we propose an anomaly detection method based on the autoencoder which encodes the multivariate time series data as 2D images designed to enhance performance. Our proposed method is validated by comparing the encoded results with the original data using four standard datasets. Five validation criteria have been used, namely, AUC, precision, recall, F1-score, and G-mean.

2. Proposed Method

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This section introduces our proposed method for improving anomaly detection performance, and discusses the datasets and evaluation metrics used in this paper. Figure 1 displays the overall structure of the proposed method. First, four time series data sets are converted into 2D images using Gramian Angular Summation Field (GASF), and then input into the autoencoder to identify anomalies by constructing the encoder and decoder. The results are then obtained from the autoencoder reconstruction values.

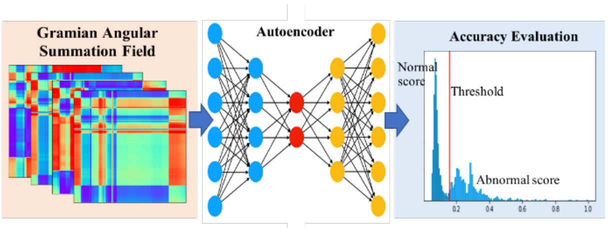

Fig. 1. Concept of the proposed method.

2.1. *Autoencoder*

Autoencoder is an unsupervised artificial neural network, which can leverage neural networks for the task of representation learning [7]. Autoencoder learns how to compress and encode data efficiently and then to reconstruct the data from the reduced encoded representation to one that is as close to the original input as possible. It consists of an encoder, a latent variable, and a decoder.

The encoder maps input data $x \in \mathbb{R}^d$ to a latent variable (code) $z \in \mathbb{R}^d$ and the decoder maps back from latent variable to input space. The autoencoder training procedure uses backpropagation to minimize the network's reconstruction loss. The loss function measures the differences between the original input and the consequent reconstruction. The loss function is defined as follows:

$$L(x,\hat{x}) = \|x-\hat{x}\|^2 \qquad (1)$$

After the training procedure, the autoencoder uses the reconstruction error as the anomaly score. The data with high anomaly scores are considered anomalies because only the normal data are used to train the autoencoder. The autoencoder will reconstruct normal data very well while failing to do so when confronted with anomalous data.

2.2. *Gramian Angular Summation Field (GASF)*

A Gramian Angular Field(GAF) [8] is an image obtained from a 1-dimensional time series, representing some temporal correlation between each time point. There are two methods available: Gramian Angular Summation Field(GASF) and Gramian Angular Difference Field. In this work, Gramian Angular Summation Field (GASF) is used to transform our time series data into 2D images, using a polar coordinate system.

In the Gramian matrix, each element is the cosine of the summation of pairwise temporal values. Given a time series $X = (x_1, x_2, ..., x_n)$ of n observations, we rescale X so that all values fall in the interval [0, 1]:

The signal is warped in the transform domain. After this, each time point in polar coordinates is compared with every other point for temporal correlation.

$$\tilde{X}_0^i = \frac{x_i - \min(X)}{\max(X) - \min(X)} \qquad (2)$$

At this point, we convert the obtained values into the polar coordinate system as follows:

$$\begin{cases} \phi = \arccos(\tilde{x}_i), & -1 \le \tilde{x}_i \le 1,\ \tilde{x}_i \in \tilde{X} \\ r = \dfrac{t_i}{N}, & t_i \in N \end{cases} \qquad (3)$$

where t_i represents the time stamp and N is a constant factor used to regularize the polar coordinate system. After transforming the rescaled time series into the polar coordinate system, GASF can be written as follows:

$$\mathrm{GASF} = \begin{bmatrix} \cos(\phi_1+\phi_1) & \cdots & \cos(\phi_1+\phi_n) \\ \cos(\phi_2+\phi_1) & \cdots & \cos(\phi_2+\phi_n) \\ \vdots & \ddots & \vdots \\ \cos(\phi_n+\phi_1) & \cdots & \cos(\phi_n+\phi_n) \end{bmatrix} \qquad (4)$$

$$\mathrm{GASF} = \tilde{X}' \cdot \tilde{X} - \sqrt{I-\tilde{X}^2}' \cdot \sqrt{I-\tilde{X}^2} \qquad (5)$$

where I is the unit row vector.

3. Experiments

In this section, we first describe the details of the datasets [9] used in our experiments, and present the performance metrics for evaluating the performance of our system.

3.1. *Datasets*

To demonstrate the effectiveness of the proposed method, we conducted experiments on four datasets: Satellite, SonyAIBORobotSurface2, ItalyPowerDemand, and Wafer. Table 1. shows the details of the datasets. We use 80% of the normal data for training, and the remaining 20% of the normal data is used for testing purposes.

Table 1. Details of the datasets.

Datasets	Length	Number of instances	Anomaly Ratio
Satellite	36	6435	0.32
SonyAIBORobotSurface2	65	980	0.38
ItalyPowerDemand	24	1096	0.49
Wafer	152	7164	0.11

3.2. *Performance Evaluation*

To evaluate the detection performance of our proposed method, we employed five metrics, namely, Area under the curve of the receiver operating characteristic (AUC), Precision, Recall, F1-Score, and G-mean [10] which are defined as follows:

$$\text{Precision} = \frac{TP}{TP+FP} \tag{6}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{7}$$

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{8}$$

$$G-mean = \sqrt{\frac{TP}{TP+FN} \times \frac{TN}{TN+FP}} \tag{9}$$

where TP is the correctly predicted anomaly, FP is the incorrectly predicted anomaly, TN is the correctly assigned normal, and FN is the incorrectly assigned normal.

4. Results and Discussion

In this section, we evaluate the proposed method for detecting anomalies in a time series data set using the Autoencoder method. First, we transform all time series data sets into 2D images using GASF. A Gramian Angular Summation Field (GASF) represents time series in a polar coordinate system and generates images by expressing polar angles as asymmetry matrix. It is an image obtained from a 1-dimensional time series, representing some temporal correlation between each time point. Also, it can preserve absolute temporal correlation.

To illustrate the advantage of transforming time-series data into two-dimensional images. We show an example of the comparison between normal and abnormal data under GASF transformation from the Wafer dataset in Figure. 2. For the Wafer dataset, each time series is labeled as abnormal or normal to identify whether the wafer process has a defect. The left side of the Figure shows the normal time series' data and the corresponding GASF images, while the right side of the Figure shows an abnormal case. As can be seen, the abnormal time series has relatively low values and two obvious spikes compared with the normal one. The corresponding GASF image of the abnormal case can be easily recognized that it has a relatively light color with two distinct crossing lines (marked by the white circles) to represent the two spikes. Therefore, the characteristics of time series data can be identified in a two-dimensional image from different features such as color, points, and lines at the corresponding locations in the image.

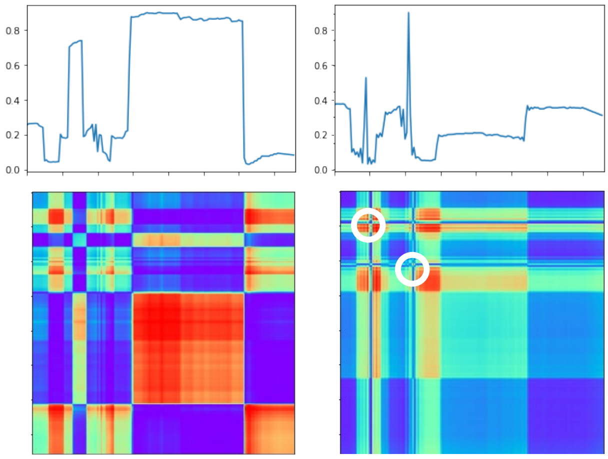

Fig. 2. The example of GASF images.

Our proposed method is trained with the normal samples, and then the model is verified using testing samples,

Table 2. Autoencoder compare of original data and our proposed method

Datasets	Original Data					Our proposed method				
	AUC	Precision	Recall	F1-Score	G-mean	AUC	Precision	Recall	F1-Score	G-mean
Satellite	0.6954	0.7075	0.6779	0.7761	0.5074	0.9869	0.7369	0.9989	0.8481	0.8325
SonyAIBORobotSurface2	0.8999	0.9043	0.7647	0.8287	0.7903	0.9640	0.9391	0.9982	0.9405	0.9171
ItalyPowerDemand	0.5917	0.7091	0.5166	0.5977	0.5263	0.9114	0.7518	0.7813	0.7282	0.8559
Wafer	0.9820	0.7349	0.9979	0.8464	0.5161	**0.9981**	**0.9820**	**0.9992**	**0.9906**	**0.9948**

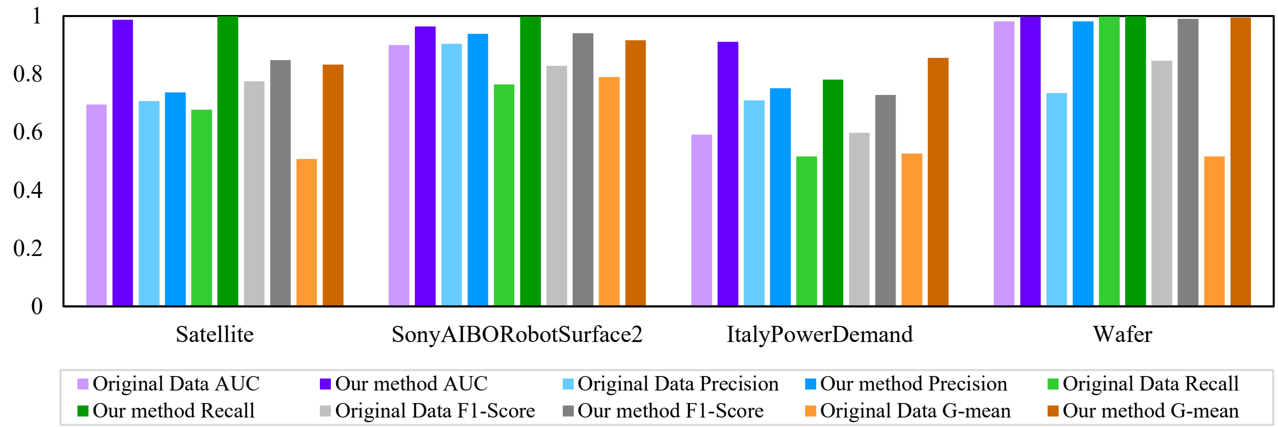

Fig. 3. All criteria comparisons of four datasets on Autoencoder

including both normal and abnormal data. We conducted our experiment to improve the anomaly detection performance in four time series data sets using AUC, precision, recall, F1-score, and G-mean criteria. Table 2. shows the summary and comparison results of anomaly detection. The bold fonts in Table 2 indicate our proposed method could improve performance relative to relying on original data. For the Wafer dataset, the F1-Score value associated with the original data was 84.64%, whereas our method achieved 99.06%. In addition, the G-mean of the original data was only 51.61% compared with 99.48% for our proposed method.

Figure 3. shows the chart of all criteria comparisons of four datasets on Autoencoder. The light color line represents the original data, and the dark color line represents our proposed method. It is quite clear that our proposed method outperforms original data.

5. Conclusion

In this paper, we have presented an anomaly detection method using an autoencoder to compare the original data represented as GASF images (2D images). Performance has been evaluated by the metrics Precision, Recall, F1-Score, and G-mean. The experiments on anomaly detection show that our proposed method could improve the accuracy of detecting anomalies for time series data. Therefore, anomaly detection in multivariate time series, judged by the criteria of AUC, precision, recall, F1-score, and G-mean, can be improved by using Gramian Angular Summation Field (GASF) image encoding.

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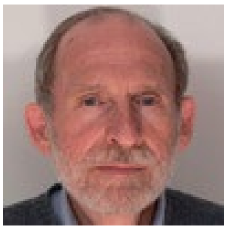

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