Anomaly detection in time series for TBM

A literatue review of the useful AD-method for Tunnuling Machines

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Abstract

Introduction

In the context of TBM, we will define anomaly detection as the detection of physical event that will provoke an unsolicited degradation of a given efficiency function. Where an efficiency function is some function that converts the machine state to a value that wants to be maximized by the user.

One can prove that this definition is a special cases of the labeling one, by labeling the decrease of the given efficiency function and retroactively the time series of sensors witch where influenced by the root cause event.

1 Secondary sources

2 Overview

3 Selection

4 Description

4.1 Graph Deviation Network (GDN)

- Core principle
  - Prediction of each sensor using the information of related sensor
  - localisation
  -

When using "distance to prediction" for AD in a multivariate settings, it's sensible to assume that related sensors have redundant information (e.g. a pressure and a extension sensors for a hydraulic cylinder). So if there measurement was put together to predict the next ones it could improve their prediction and so reduce the detection threshold. This is a base idea of the GDN architecture in [**?**]. Mark the related sensor in a directed Graph and apply an attention layer on the past measurement of the neighborhoods to predict the next ones. Here is some short assertion and nice propriety of this approach :

- Even if every sensor of the TBM are in the graph, the AD is still localize to each sensor.
- The training data is assume to be free of anomaly.
- Prior knowledge of relation between sensor can be embedded in the graph by restricted some relationship. This can lower the complexity and the time of training.

To test their method the authors used dataset of simulated attack on water treatment physical test-bed systems, the Secure Water Treatment (SWaT) and Water Distribution (WADI) dataset. As a base line they use other method which we discus in other Section.

	SWaT			WADI		
Method	Prec	Rec	F1	Prec	Rec	F1
PCA	24.92	21.63	0.23	39.53	5.63	0.10
KNN	7.83	7.83	0.08	7.76	7.75	0.08
FB	10.17	10.17	0.10	8.60	8.60	0.09
AE	72.63	52.63	0.61	34.35	34.35	0.34
DAGMM	27.46	69.52	0.39	54.44	26.99	0.36
LSTM-VAE	96.24	59.91	0.74	87.79	14.45	0.25
MAD-GAN	98.97	63.74	0.77	41.44	33.92	0.37
GDN	**99.35**	**68.12**	**0.81**	**97.50**	**40.19**	**0.57**

Table 1: Anomaly detection accuracy in terms of precision(%), recall(%), and F1-score, on two datasets with ground-truth labelled anomalies. Part of the results are from [**?**].

5 Evaluation

Conclusion