

Anomaly detection in time series for Tunneling Boring Machines

A literary review of useful method

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Introduction

By default, Tunnel Boring Machines (TBMs) are complicated technical objects and involved a lot of technologies working together. Any defect in the chain could stop the entire machine. Therefore, detecting those before they become a real issue can save a lot of time and resources. Fortunately, the number of sensors on the machines keeps raising and thanks to platforms like Herrenknecht.Connected [9], their data can be accessed anywhere by any authorized user. These data must carry a lot of information regarding the state of the machine, which begs the question of how to extract it to detect anomalies. At the time of writing, the task is mostly done by experienced users of the TBM, e.g. a weird noise in the hydraulic pack, an odd torque increase on one of the main drive motors, and so on. This method is clearly limited and uses only a small portion of the available data stream. Despite this, the problem of anomaly detection is quite old, and with the rise of machine learning technic, it keeps getting better.

Therefore, in this paper, we will, have a first look of at the literary landscape of Anomaly detection (AD) methods. First, let's define exactly what we mean by that, given a multivariate time series:

$$\mathcal{X} = (\mathbf{x}_1, \dots, \mathbf{x}_t, \dots, \mathbf{x}_T) \in \mathbb{R}^{N \times T} \quad (1)$$

with N the number of sensors and T the number of temporal indices. The method \mathcal{M} will return a binary category for each data point telling where and when there is anomalies, ie:

$$\mathcal{M} : \mathbb{R}^{N \times T} \rightarrow \{0, 1\}^{N \times T} . \quad (2)$$

We need to address some loose ends with this definition. First, in most cases, there is no already labeled data to train the method on, and labeling it by hand is not feasible. So the method must be unsupervised, which raises the need for a systemic definition of anomalies. Most papers consider the training data to be normal and define some anomaly score, which tells how far away the new data is. Here, the methods will, be categorized based on the way this score is defined.

In our context, the training data is stems from historic tunnel projects, which contains anomalies. Therefore, we will also discuss some papers which tried to address this issue by modifying the methods.

1 Overview

AD methods can be categorized in many ways [6]. In this paper is divided in two parts (cf Figure 1), general methods and useful

tricks to improve theses. The former represents general ways to solve the AD problem. It is composed of three categories: forecasting (Sec 1.1), clustering (Sec 1.2) and index monitoring (Sec. 1.3). The latter are so-called add-ons (Sec 1.4). The papers in this category present an AD method with some tricks that, in our minds can be applied to any method to improve it.

1.1 Forecasting Methods

When working with some equipment, you know it so well that, if asked, you could almost predict the sound it will make in the near future. But if suddenly the sound doesn't match your expectations you know there are some things wrong. That is the core idea for the forecasting method, predict the near future using some generative method and if the error goes over some threshold, the data point is labeled as an anomaly. Example of those forecasting technics may be LSTM [10] or using TCN [1].

1.2 Clustering method

While storing metric screws in the warehouse, someone picks up an imperial one, he wants to find any box to put it in. Therefore he will conclude there was an error in the shipment, even if he didn't know this type of screw. This is the main idea for the clustering method, define clusters, if a new data point can't fit in one of them, it is labeled as an anomaly. There are multiple ways to define the cluster. A good part uses some defined distance [7] function and uses a variant of K-nearest-neighbor (KNN) [13]. Similarly, use the density of the data point in relation to the training data, which will give less, strict categorizes [3]. Another method is to estimate the probability density function (PDF) and put a threshold on low values [2].

1.3 Index monitoring

After assembly, the disks cutters there are put under pressure for some time. When the time is up, the pressure is measured, if the pressure is too low, there is a problem somewhere. This is the intuition behind index monitoring method, define some function with an acceptable range of normal values, if the values are outside the range it's marked as an anomaly. This technic is one of the oldest, simplest and most used in the manufacturing industries, in this context is referred as Control chart [15]. Another example of application is [11] which use a modified wavelet transform to define a Health Index to monitor bearings.

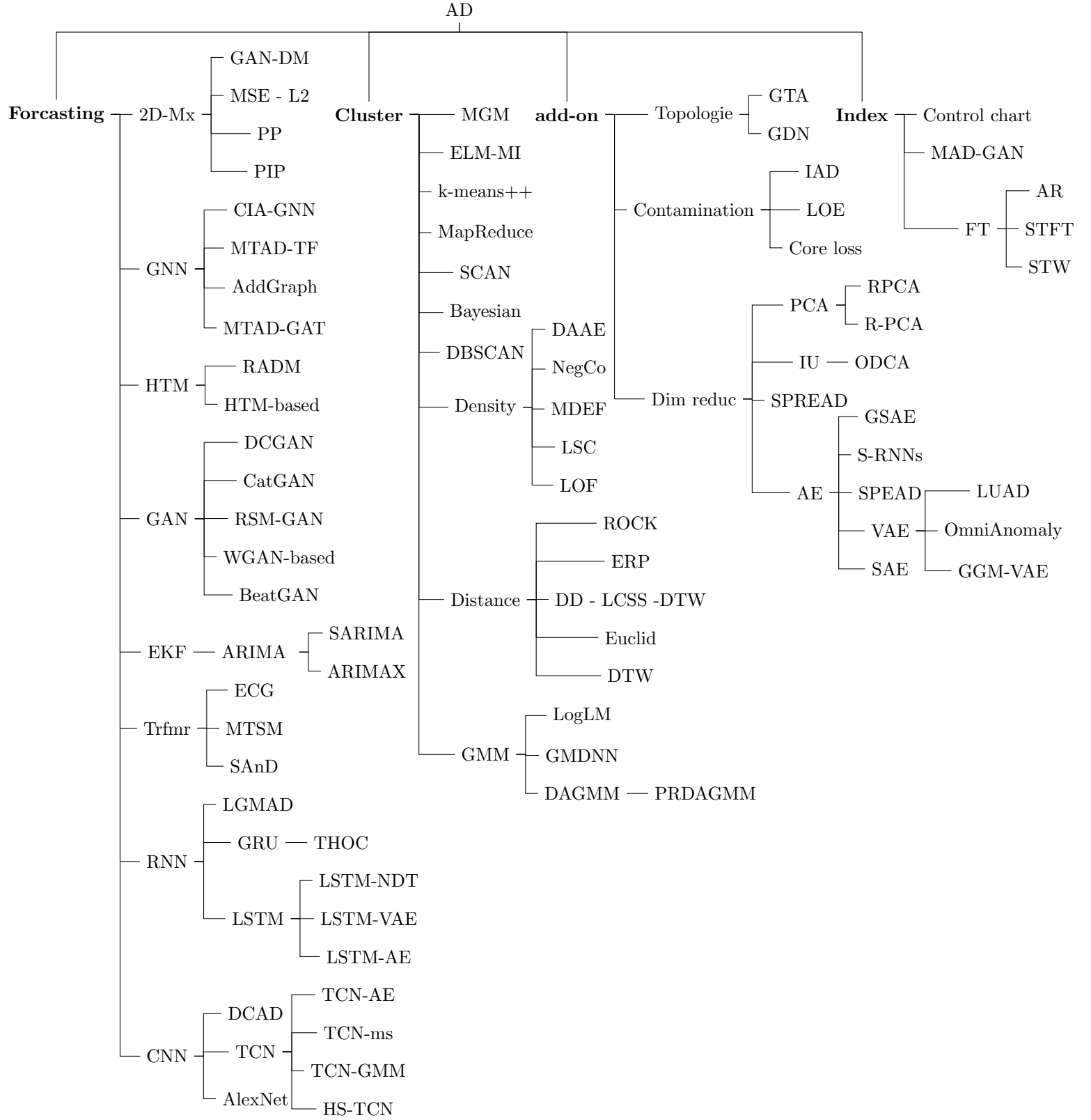


Figure 1: Anomaly detection method categorization

1.4 Add-ones

In order to improve those techniques and solve issues intrinsic to the TBM case, here are some interesting solutions.

Topology, TBM AD is intrinsically a multivariate problem (ie there is more than one sensor on the machine). And it is safe to assume that the anomaly information for some problems is carried by multiple sensors. For example, if there is a defective sensor, the others want to raise any anomaly, which will greatly help to pin the root cause down. This what [8] and [4] did so by introducing a directed graph to model the relationship between sensors. This information was then used, in these papers, to do forecasting using attention techniques.

Contamination, the training data for those models will surely be some already-bore tunnel data. During those bores, by Murphy’s law, at some point, some things went wrong. The issue is that most methods assume an anomaly free dataset. This is why [12] [5] [16] proposed some modifications to the training steps to deal with this contamination. To do so, they generally modify the loss function to account for the uncertainty of the data and improve this uncertainty iteratively.

Dimension reduction, a large quantity of sensors, with a quite small data rate, even with a small time window can make the input dimension of the model certainly significant. This can render the training hard and sensitive to noise. to solve this issue, most papers use some kind of dimension reduction. For example, [2] uses an AE and a modified reconstruction error concatenated with the latent vector as an input to a GMM. Or [14] used a LSTM as an AE to do forecasting.

2 Description

2.1 Graph Deviation Network (GDN)

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 [8]. 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)

Method	SWaT			WADI		
	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. Table from [8].

dataset. As a base line they use other method which we discuss in other Section.

Conclusion

In this paper we have seen that there is three main ways to do AD, forecasting, clustering, index monitoring. It can be observed that the dataset usually used to compare the forecasting methods (cf Table 1) may not be generalized to TBM. The reasoning is that those data set is homogenous in time, when the TBM’s ones highly depend on a varying geology. We also found, some ways to improve those methods using topologies information, contamination handling and dimension reduction. The aim of future works will be to test those methods on actual TBM data to see how well they work, and under which condition.

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Appendices

A Acronyms

TBM	Tunnel Boring Machine
2D-Mx	2D matrix
AD	Anomaly detection
AE	Autoencoder
AR	Autoregression - Health index
ARIMA	Auto-regressive Integrated Moving-average
ARIMAX	ARIMA exogenous
ATF-UAD	Adversarial Time-Frequency Reconstruction Network for Unsupervised Anomaly Detection
AlexNet	AlexNet
Bayesian	Bayesian network
CIA-GNN	Correlation- and Interaction-Aware Anomaly Detection
CNN	Convolutional neural networks
Classical	Classical methods
Cluster	Clustering-based methods
Contamination	Deal with contaminated training data for UAD
Control chart	Control chart
Core loss	Core loss
Cube	data cube technique
DAAE	Distribution alignment autoencoder
DBSCAN	Density-based spatial clustering of applications with noise
DCAD	Densely Contrastive Anomaly Detection
DCGAN	multi-time scale deep convolutional generative adversarial network
DD - LCSS -DTW	Derivative distance with DTW and LCSS
DTW	Dynamic time warping
Deep	Deep leaning
Density	Density-based methods
Deviation	Data deviation AD
Dim reduc	Dimensional reduction
Distance	Distance-based methods
EKF	Extended Kalman Filter

ELM-MI	Extreme learning machine and mutual information
ERP	Edit Distance on Real Sequence
Euclid	Euclidean distance
FT	Fourier transform
Forecasting	Forecasting
GAN	Generative adversarial network
GAN-DM	Distance image GAN
GDN	Graph Deviation Network
GMDNN	Gaussian mixeddensity neural network
GMM	Gaussian mixture model
GNN	Graph Neural Network
GRU	Gated recurrent units
GSAE	Attention graph stacked autoencoder
HTM	Hierarchical temporal memory
IAD	Iterative Anomaly Detection
ILSFS	Knowledge-based target variables into inner feature selectors
IU	Independent univariate
Index	Index monitoring
LOE	Latent Outlier Exposure
LOF	local outlier factor
LSC	local sparsity coefficient
LSTM	Long short term memory neural networks
LUAD	Lightweight unsupervised anomaly detection
Linear	Linear model-based methods
LogLM	Log-linear mixture
MDEF	multi-granularity deviation factor
MGM	multivariate Gaussian Models
MSE - L2	Least squard method with L2 regularisation
MVDD	Multiscale support vector data description
NegCo	Negative correlation
OCSVM	One-class support vector machine
PCA	Principal component analysis
PIP	Pairwise inner-product

PP	Pairwise phase
PRDAGMM	Pyramid Reconstruction Assisted Deep Autoencoding Gaussian Mixture Model
R-PCA	recursive principal component analysis
RNN	Recurrent neural networks
RP-LREC	Recurrence plot with local recurrence rates
RPCA	Robust PCA
SAE	Stacked autoencoder
SARIMA	Seasonal ARIMA
SHAP	Shapley Additive explanation
SPREAD	Sparse Recurrent Neural Network based Anomaly Detection
STW	Stationary wavelet transform
TCN	Temporal convolutional networks
THOC	Temporal hierarchical one class network
Topologie	Multivariate topologies
Tree	Decision tree
Trfmr	Transformer
VAE	Variational Autoencoder
VAR	Vector autoregression
Vector	Support vector machines
add-on	Methode to addapt existimg techniaque to solve specific problem
KNN	K-nearest-neighbor