

Online change detection techniques in time series: An overview

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Abstract— Time-series change detection has been studied in several fields. From sensor data, engineering systems, medical diagnosis, and financial markets to user actions on a network, huge amounts of temporal data are generated. There is a need for a clear separation between normal and abnormal behaviour of the system in order to investigate causes or forecast change. Characteristics include irregularities, deviations, anomalies, outliers, novelties or surprising patterns. The efficient detection of such patterns is challenging, especially when constraints need to be taken into account, such as the data velocity, volume, limited time for reacting to events, and the details of the temporal sequence.

This paper reviews the main techniques for time series change point detection, focusing on online methods. Performance criteria including complexity, time granularity, and robustness is used to compare techniques, followed by a discussion about current challenges and open issues.

Keywords— Online change detection, abnormality detection, time series segmentation

I. INTRODUCTION

Online change detection has become crucial with the improvement of technologies and the era of internet 4.0. In fact, recent decades have seen a rapid growth of data generation and retention. This has led to the emergence of new challenges as traditional computational techniques need to keep pace with such growth. These challenges are important in streaming analytics and especially for time series change detection, when constraints such as online or real-time requirements, data velocity and volume are added.

Change detection has been the subject of studies for decades [1]. It is often referred to as anomaly, event, novelty, extreme value, outlier, or irregularities detection. Hawkins defined change detection as observation that significantly deviates from the others, suggesting that an internal or external change occurred, affecting the system [2]. Keogh shows that this definition does not sufficiently cover cases when the interest is in looking for surprising patterns [3], [4]. The complete details of these discussions is beyond the scope of this paper, as it focuses on the detection techniques, but the key point in finding change points is looking for efficient methods that seek out where the shifts in structural patterns occur.

The notion of real-time depends on the evolving context. For instance, targeted advertisements may require a few seconds as time latency, whereas in the stock trading or in autonomous vehicle environment, this latency constraints may be reduced to

a scale of milliseconds. Moreover, operation condition monitoring may be in hours and the degradation patterns forecasted over days. Some authors consider overlapping definitions such as near-time or online, whereby time latency constraints are more permissive [1], [5].

Time series online change detection techniques are to be distinguished from the traditional methods, in relation to the sequential order of the data and often an underlying time constant. In real applications context, the processes generating such flux of streaming data may evolve through time. Hence the observed time series are often nonlinear, aperiodic and follow unknown distribution. This brings additional challenge in terms of model building and data analysis.

Online change detection is important in various domains. Examples are as follows.

- In the medical domain, real-time abnormality detection is useful to assess patient health and therefore allow quick diagnostics and decision making. Examples include electrocardiograms and heart rate monitoring [6], [7].
- In the engineering domain, monitoring devices release huge amount of time series data, which often need quick change detection to trigger alerts for systems diagnosis, or to schedule maintenance activities [8]. A typical example is vehicle engine oil temperature monitoring in which real-time outlier detection may help to avoid catastrophic damage and accidents [9].

Others areas include the financial sector (trading, currency variation, customer transaction) [10] or abnormal user actions detection (e.g., hacker's intrusion into the network) [11], speech recognition [12], [13], and image or video analysis [14], [15]. This paper explores the general characteristics of online change point detection and describes appropriate methods. It then compares the investigated techniques given criteria such as data structure complexity, limitations and time granularity. Finally, it concludes with challenges and gaps in the research, and opportunities for future directions.

II. BACKGROUND

The motivation of this work arose when studying online data from engines and doors on trains. Such nonlinear systems are complex to analyse as they involve many local parameters and external effects. It is therefore convenient to find structural

change points for efficient analysis. Several reviews of change detection exist in the literature.

“Y.Ban et al [16]” reviewed change detection methods focusing on multitemporal remote sensing change with both optical and synthetic aperture image. Approaches such as supervised, unsupervised, object-based, context-based methods were reviewed. Analogous review has been done for image analysis [17] [18], [19], [20], [21]. The authors showed that supervised and unsupervised methods were widely used for image analysis and more analysis need to be done with large real datasets.

“Truong, Charles et al [22]” provided a selective review of change detection methods. In the latter, a comprehensive understanding of the global optimisation model for change detection and search algorithms are highlighted. Most of the algorithms are offline methods. Hence, those may require users to know the full length of the datasets, the number of change, or the process distribution. Similar review of the techniques exist [5], [21], one covering more the online aspect [23]. All tend to agree that parametric methods are less robust than the nonparametric ones. In temporal streaming data, they are less reviews of change detection technique used. However, it can be observed that industrial domains extensively use signal processing methods, fuzzy based models, mathematical [24] model based, and classical statistics tests for change detection [25]. In the financial domain, attention is paid more on the forecasting models, and unsupervised models [26], [10].

There is a poor focus on the online methods and current literature does not provides a clear explanation of the issues. The contribution of this paper is to help practitioners for clear understanding of change detection, describes each class techniques advantages and drawbacks, and highlight gaps for future research purpose.

Fig. 1 below represents an engine speed in revolutions per minute (rpm) and the charge air pressure in pounds per square inch (psi) over time. The vehicle travel pattern includes start up, acceleration, deceleration, gear changes, constant speed, and shutdown. In such a scenario, the applicability of change detection has dual relevance. On the one hand it identifies a change in the operating mode (e.g. from acceleration, to cruising or coasting, to braking or deceleration). On the other hand, within each of these different operating regimes, change detection may apply to abnormal or at least rare conditions. In typical engineering monitoring systems, change detection is broken down into intermediate events, while particular events or event sequences may correspond to operating mode changes, or emergence of abnormal conditions. Therefore detecting change points is a key for condition monitoring and therefore for detecting, diagnosing and predicting evolving faults.

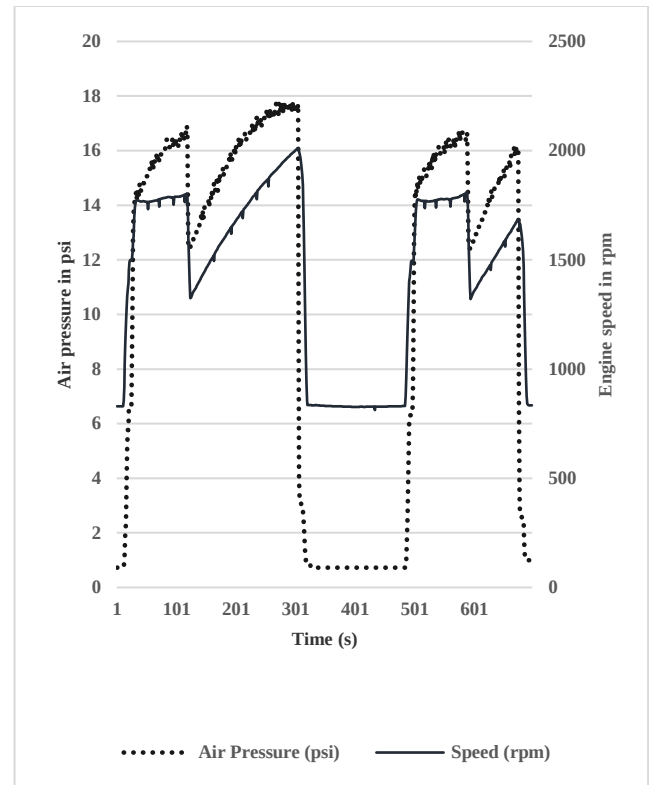


Fig. 1: Engine frequency over time

Various approaches and techniques have been proposed to tackle streaming data change detection. Fig. 2 summarises generic workflow of time series change detection used in the literature. The processing step techniques handle data quality and feature processing issues. This step includes data cleaning and data imputation then, relevant feature extraction and selection. Change detection techniques can be classified into two main categories: supervised and unsupervised techniques. Recent research focused on hybrid approaches, enabling the growth of a third category, namely semi-supervised learning. Each technique computes scores or assigns class labels, by which a decision on whether a change has occurred at a specific point in time is made. However, detection algorithms may suffer from performance limitations such as stability against plasticity and sensitivity against robustness.

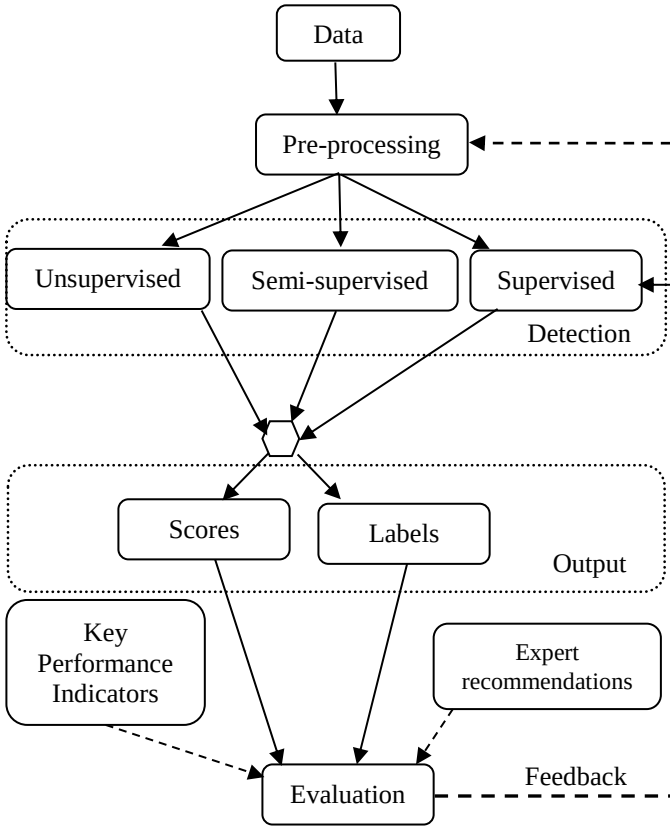


Fig. 2 Generic framework for online time series change detection

A. Data

The nature of the data plays an important role in time series analysis, especially for change point detection. It therefore deeply influences the choices for determining which data management framework and techniques would be appropriate to use. Temporal data are often organised in data points. Each data point contains the same number of attributes, known as the dimension of the time series. Each attribute value at each observation (also known as instance) could be simple, such as text, numerical and categorical, or complex, such as spatial, images, and videos. Real data are often mixed, making analysis more complex. Beyond the nature of the data, the quality, volume, velocity, variety and veracity, which are commonly recognised as the challenging characteristics of big data, are to be taken into consideration when dealing with change detection. Examples of these issues include inconsistencies, imbalance, reception rate, poorly defined and missing data.

B. Pre-processing

This is a step influenced by the change detection techniques used. Change point detection models may not need processing, as long as raw data quality and structure are enough for the models to perform accurately. Comprehensive investigations of data imputation techniques can be found in [27] whilst feature extraction and selection techniques are discussed in [28], [29]. The development of new concepts, services and technologies has improved the computation in large scale processing techniques, helping to reduce the complexity of the problem,

and has allowed traditional methods to perform efficiently. Map-Reduce and similar concepts are widely implemented in data management software (e.g., Hadoop [30], Spark [30], and H2O [31]). Likewise, cloud computing as a service (e.g. OpenStack [32], or Open Cloud Computing Interface [33]) and many distributed programming environments are easily implementable or available online, enabling data integration through simple applications interfaces. However, there are open issues in this area that need more investigation. These include:

- instance reduction: it is especially complex to reduce time series data instances without losing performance, due to the sequential order of the data. Instance selection methods by correlation analysis, principal component analysis (PCA) based methods, similarity and dissimilarity measure are used for instance reduction. In the case of temporal image analysis some authors recommend PCA-based methods [18];
- missing values imputation: finding the “best” value to replace missing values, or choosing useless rows for deletion, are challenging. Interpolation, model fitting and forecasting models are used to handle such issues;
- uncertainty reduction (noise reduction): reducing noise in time series data is a complex task and depends on the characteristics of the noise; while simple noise may be considered as outliers or extreme values, complex noise needs more sophistication. Filtering and smoothing methods such as moving average, Gaussian filtering, Geometric filtering are suitable for time series noise reduction.

Additionally, choosing the right techniques and combining them for optimal performance remains challenging. This may require joining contextual knowledge of the system, the data management systems and infrastructure used, and the analytics in a data fusion framework.

C. Detection

Online change point detection (OCPD) algorithms often operate in parallel with the monitoring system, processing every incoming data point to decide whether or not a change occurs [34]. In fact, most algorithms require posterior data for accurate decision making. Posterior data may have sufficient fluctuation to characterise a change. Hence, this creates a response lag, often described in the literature as ϵ -real-time algorithms [23]. Statistical algorithms can be classified into parametric and nonparametric, according to the assumptions made about the nature of the data. Whilst parametric methods specify the form of the behaviour and parameters learned from the training data, nonparametric methods do not make any preliminary assumption of the form. Studies show that for online OCPD purposes, even if nonparametric algorithms are hungry in memory (i.e. need all the available data in memory while inference making), they tend to have better results, are accurate with large windows, and less computationally expensive [23]. Change detection techniques are highlighted in section III.

D. Output

Algorithmic outputs for OCPD are typically class labels or scores. Labels refer to a finite discrete class, and scores can be seen as continuous values. Therefore, classes offer a binary classification, where scores may reflect a gradual transition between states or an uncertainty about them. Scores are more flexible for change point detection even if they raise the decision problem of which is the best threshold, beyond which a change may arise. At this stage, key performance indicators (KPI) and expert knowledge are often used to improve the decision.

E. Evaluation

Various metrics have been developed to evaluate change point detection. These metrics include, for accuracy performance, some statistics such as root mean squared error (RMSE), precision, recall, mean absolute error (MAE), f-scores, area under the curve (AUC) and mean signed difference (MSD), as well as static pattern classification such as the confusion matrix and its derivatives. Output performance is also often assessed by an expert recommendation system. In engineering systems, where expert knowledge plays a key role, recommendations and metrics are combined for efficient accuracy. For online detection purposes the complexity of the algorithm plays an important key role in the evaluation. Polynomial complexity is preferred to exponential complexity, which can be very time consuming for less than one percent accuracy gain when increasing the window size. There is a need in such context to define metrics that take into account the time delay with respect to criteria such as data variety (spatio-temporal), velocity (time granularity), and volume (dimension), which current researches rarely cover.

III. CHANGE DETECTION TECHNIQUES

Many techniques have been developed, adapted and enhanced for change point detection. Here, a few basic techniques commonly used in the literature are highlighted. These techniques include machine learning supervised, unsupervised and semi-supervised techniques.

A. Supervised models

Supervised methods involve assigning observations to discrete (classification) or continuous (regression) classes. For online change detection, these methods often need models to be trained offline with labelled data before use. Hence, during the training phase, adequate and diverse (including normal and abnormal) data are required for accurate change detection in the model. Many classifiers exist for supervised learning. Recent research has used decision trees such as logistic regression [35], naive Bayes, support vector machine (SVM) [1], hidden Markov model (HMM) [36] and linear regression models. Real data are often imbalanced (not identically distributed within classes). This is a major issue for supervised methods even if techniques have been developed to tackle it. Another issue is the inability of supervised methods to handle new classes. Real data such as sensor data in engineering systems always contains unseen behaviour because the context and environment are continuously evolving.

B. Unsupervised models

Unsupervised methods are able to discover patterns in unlabelled data. They are interesting for change point detection because of their ability to discover new change in a stream without prior training. Recent models used can be classified into three main approaches, namely statistical methods, clustering methods and rule based methods.

Statistical methods include hypothesis testing and signal processing. This approach tends to extract properties such as the mean, standard deviation, skewness, kurtosis, and root mean squared (RMS) of the data, and looks for the transition point by building a hypothesis. Methods such as the cumulative sum (CUSUM) [37], [38], Martingale test [15], [39], minimax [40], auto-regressive model (AR) [41], and Bayesian inference [42], [43], [44] have been used for OCPD. For some processes, it can be useful to transform data from the time domain to frequency domain (Fourier Transform) or time frequency domain (wavelet transform or other) for change detection. The window basis [45], incremental fast Fourier transform (FFT), and the Haar wavelet [46] have been widely used for online change point detection.

Clustering methods assign the data point, or a sequence of data points, to existing or newly created clusters over time. Change is therefore detected when consecutive data points do not belong to the same cluster. Sliding window and bottom-up (SWAB) based algorithms [3], [47], shapelet methods [48], model fitting methods [49], and the minimum description length (MDL) method [48], have been used in various domains for change point detection.

Rule based methods map observations with specific function or trigger rules, to detect whether or not changes occur. They are often associated with a likelihood or a ratio. Models may be distance based, such as similarity and dissimilarity distance [49], [50], fuzzy detection [51], kernel based rule methods and likelihood ratio methods.

Although it has been shown that these methods performed efficiently under specific contexts and datasets, important challenges still need to be addressed. One challenge is to adapt these methods for distributed analysis. Most of the algorithms need to join the data into a main stream for analysis. Therefore having models that can perform efficiently near the data source, and transmit their results to wider systems, will reduce time consumption and costs, and improve performance. Another issue that needs to be addressed is the ability of models to handle uncertainty. The processing step cost, in terms of performance and capability, will show its worth in reduction of complexity of the overall process.

C. Semi-supervised models

Due to the costs in labelling, such models are designed to handle partially labelled data [52]. To date, not many semi-supervised algorithms have been used for change detection in general. One reason may be that pseudo-labelling is used during the processing step (see Fig. 2) with the results published as supervised models. Another reason may be the limited amount of data available for research purposes. However, semi-

supervised learning models combined with neural networks [53] or sparse fusion and constrained k-means [54], have been used for change detection in sensing images, but the temporal complexity costs for the training and the tests are not highlighted. One of the main issues in such modelling techniques is that there are no prior knowledge assumptions underlying the relationship between the labelled data and the unlabelled data. This can often lead to more inaccurate results in the analysis than just keeping the labelled data [49].

Table 1 summaries several selective techniques that can be used for real-time, online or near-time purpose with their advantages and drawbacks.

IV. TECHNIQUES EVALUATION

It is difficult to compare online time series change detection models as they may not be built on the same assumptions and may not handle uncertainty at the same level. For instance, detecting a change with a probability of 90% in the manufacturing domain may be enough, whilst in physics more accurate results may be required (99.99%). Likewise, detecting a change with a delay of 30 minutes, for instance, may be interesting for door faults on a train, whilst the same delay may be problematic for autonomous vehicle cameras.

Table 2 below presents techniques commonly used for online change point detection in various areas. They are compared using several metrics.

- Parametric (P) /nonparametric (N-P): indicates if the techniques use parameters or not. Some techniques have both implementations.
- Complexity (Cost): the average time complexity taken to run the techniques.
- Incremental: ability of the techniques to learn or predict new pieces of coming data without restarting everything.
- Limitation: assumption under which the techniques perform. Some techniques for example do not have any limitation, while some may need the data to be stationary, seasonal, or nonstationary.
- Forgetting factor (FF): at a level of depth, past data may have less influence in the in the coming change points. FF is the ability of the technique to forget past data.
- Robustness: the capacity of the methods to perform under noise.

V. CONCLUSION, CHALLENGE AND FUTURE WORK

In this paper, methods for online change point detection have been highlighted. Common performance indicators used in this area were presented, with a comparison of the techniques showing their advantages and drawbacks. Since the growth of “big data”, research related to online change point detection has realised significant progress. However there are still open challenges that need more investigation.

- Model performance: one challenge is the reduction in the complexity of the models. Real world data often need change detection points on time for quick decision making. Most algorithms suffer from high complexity (non-polynomial complexity). Moreover, parameter estimation is an important issue. Most parametric models remain unused because no formal parameter estimation methods exists. Hence, investigations on these issues are crucial.
- Data challenges: more research needs to be undertaken for online multidimensional change detection using real applications data. Few methods exist for this purpose and those that do suffer from robustness and scalability. Likewise, investigation is needed for nonstationary time series and unequally distributed time series.
- Context handling: another issue is that time series data are mostly contextual. Therefore more investigation should be undertaken to combine knowledge modelling and change detection techniques for better models. Interesting area of investigations include change detection interpretation and estimation.
- Feedbacks modeling change detection: no much research is undertaken to take into account an external or internal feedbacks to improve through time the accuracy of the change detection.

Our future work will investigate change detection in large multidimensional time series to detect abnormal change in railway engines.

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Techniques	Examples	Advantages	Drawbacks
Neural Network based	[55], [56], [57], [58], [59], [60]	<ul style="list-style-type: none"> - adapted to nonlinear temporal data - accurate when enough data is used in the training stage - prior assumption free (no prior assumption on the distribution of the process) 	<ul style="list-style-type: none"> - require huge amount of data - huge training time computational cost
likelihood and probability based	[61], [62], [63],[64],[65], [66], [67]	<ul style="list-style-type: none"> - More applicable online and concept drift change detection 	<ul style="list-style-type: none"> - host of the models assumes that the process id i.i.d
Clustering based	[68], [69], [70], [71], [72], [73], [74]	<ul style="list-style-type: none"> - can handle unbalanced dataset - can handle nonlinear classification with appropriate kernel function 	<ul style="list-style-type: none"> - high computational cost depending on the metric used. - may require multidimensional scaling for more accurate results - less accurate results on huge clusters
SVM based methods	[75], [76], [77]	<ul style="list-style-type: none"> - less overfitting problems - robustness to noise - easy to implement 	<ul style="list-style-type: none"> - difficult on multiclass classifiers - need to choose the right kernel function - time cost during the training phase (labelling the data, generating unbalanced datasets and training)
Decision Tree based methods	[35],[78]	<ul style="list-style-type: none"> - automatic rules - easy to implement 	<ul style="list-style-type: none"> - overfitting problems, can lead to high false alarm rate - computational cost and less accuracy on sparse dataset
Hybrid model	[79],[80]	<ul style="list-style-type: none"> - accurate results - less false alarms rates generation depending on the methods 	<ul style="list-style-type: none"> - high computational time cost when complex methods are used

Table 1 several online techniques advantages and drawbacks

Category	Methods	Summary	FF	P/N-P	Inc	Cost	Limitation	TG	robustness
Unsupervised	Mu-sigma	Mean and standard deviation threshold based method [81], [82]	✓	P	✓	$O(n)$	NL	µsec	✓
	CUSUM	Cumulative sum [37], [38],[62]		N-P	✓	$O(n^2)$	NL	µsec	
	AR	Auto Regressive models [41]	✓	P	✓	$O(n^3)$	ST/NL	sec	
	Martingale	Martingale tests [15], [39]		P	✓	$O(Kn^2)$	ST	sec	✓
	t-digest	Streaming percentile based detection [83]	✓	N-P				µsec	
	KLIEP	Kullback-Leibler importance estimation procedure [84]		P/N-P		$O(n^2)$	P=N-ST NP=NL		
	Bayesian	Online Bayesian probabilities methods [42], [43], [44]	✓	P	✓	$O(n)$	i.i.d		
	WT	Wavelet Transform [46]		N-P			NL		
	FFT	Fast Fourier Transform [85]		N-P			NL		
	KCP	Kernel Change Point [86]		N-P		$O(n^3)$	i.i.d		
	SWAB	Sliding Window And Bottom-up [3], [47]		P		$O(Kn)$	NL	msec	
Supervised	MF	Model fitting [87]	✓	P	✓		NL	sec	
	HMM	Hidden Markov Models [88], [89]		P	✓	TC	NL		
	KNN	K- Nearest Neighbour [90]		N-P		TC	NL		
	SVM	Support Vector Machine [75], [76]		P		TC	NL		✓
	LR	Logistic regression [91]		P	✓	TC	NL		

Table 2 Online change detection techniques. P/N-P: Parametric/Non-Parametric, Inc.: can be incremental, Cost: computational time complexity, TC: Training Cost, TG: Time Granularity, NL: No Limitation, ST/N-ST: Stationarity/Non-Stationarity, i.i.d: Independent and Identically Distributed.

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